EXPLORING FACTORS THAT INFLUENCE PROGRESSION OF DIABETES COMPLICATIONS: A STUDY OF MEDICARE AND DUAL ELIGIBLE BENEFICIARIES

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Ramzi Abujamra

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Stephen T. Parente, PhD

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Dedicated to my father, Dr. Fawzi Abujamra, MD.

Abstract

This dissertation will explore the factors that influence development of Diabetes complications for Medicare and dual eligible beneficiaries, for three Diabetes complications: retinopathy, nephropathy and neuropathy. Both predictive and explanatory models are explored. Predictive models focus on finding factors most predictive of Diabetes complications among Medicare and dual eligible beneficiaries. Explanatory models seek to answer the three hypothesis of this study. The first hypothesis states that higher treatment investment is associated with lower rates of Diabetes complications in Medicare and dual eligible beneficiaries. The second hypothesis states that physicians who are specialists (vs. primary care) and urban (vs. rural) are associated with lower rates of Diabetes complications among Medicare and dual eligible beneficiaries. Finally, the third hypothesis associates higher patient total cost sharing with improvement in Diabetes complications outcomes among Medicare and dual eligible beneficiaries. For dual eligible beneficiaries, patient cost sharing is defined as state Medicaid investment per beneficiary for the state where each beneficiary resides in.

The results for the predictive models are strongest for nephropathy complication, and weakest for retinopathy complication. The results for the explanatory models show that for the first hypothesis, nephropathy has lower rate of Diabetes complication for higher total treatment investment. For the second hypothesis, rural providers have lower rate of

Diabetes complications for nephropathy (non-dual beneficiaries) and neuropathy (for dual beneficiaries). Also, primary care providers have lower rates of Diabetes complication for retinopathy and neuropathy (non-dual beneficiaries) and retinopathy (dual beneficiaries). For neuropathy, specialists have lower rates of Diabetes complications (for non-dual beneficiaries). Finally, for the third hypothesis, no complications are associated with lower Diabetes complication rates with higher patient total cost sharing for non-dual beneficiaries. For dual beneficiaries, retinopathy and nephropathy (to a lesser extent) show evidence of lower Diabetes complication rates with higher State Medicaid investment per beneficiary. Model performance results based on the C-statistic are moderate overall, with nephropathy showing the best performance and retinopathy the lowest performing among all of the Diabetes complications.

Table of Contents

Dedication…….....…....i
Abstract…….iii
List of Tables……...……vii
List of Figures……x
1 Introduction……..……...….1
1.1 Study Description……...1
1.2 Specific Aims, Including Statement of Hypothesis……...…..5
2 Literature Review …….....7
2.1 Diabetes…….…..7
2.2 Diabetes Complications…….....8
2.3 Diabetes Comorbidities…….……....9
2.4 Prevention of Complications…….…..11
2.4.1 Treatment Investment…….…….15
2.4.2 Provider Type……..16
2.4.3 Patient Cost Sharing……16
2.5 Study Design ……,……...17
2.5.1 Prediction……19
3 Methods……21
3.1 Data Source…….....21
3.2 Data Collection…….23
3.3 Sample Selection……..24
3.4 Model Design and Variables…….……..32
3.4.1 Independent Variables……...….32
3.4.1.1 Socio-Demographic Variables…….…….32
3.4.1.1.1 Age……..…….…….32
3.4.1.1.2 Sex…….……34
3.4.1.1.3 Race…….…..…34
3.4.1.2 Comorbidity Risk Factors…….35
3.4.1.3 Health Utilization Variables…….....37
3.4.1.3.1 Inpatient Length of Stay……...….37
3.4.1.3.2 Inpatient and Outpatient Admissions and Total Office Visits…..39
3.4.1.3.3 Skilled Nursing Facility Admission……..……40

3.4.1.4 Analytical Factors……..…...41
3.4.1.4.1 Total Cost of Treatment……..……..42
3.4.1.4.2 Physician Factors……..46
3.4.1.4.2.1 Primary vs. Specialty…….……..48
3.4.1.4.2.2 Urban vs. Rural……52
3.4.1.4.3 Patient Cost Sharing…….….54
3.4.1.4.3.1 Non-Dual Beneficiaries…….…..54
3.4.1.4.3.2 Dual Beneficiaries…….……...….58
3.4.2 Outcome Variables…….……..…60
4 Model……..…..…63
4.1 Predictive Model……...……64
4.2 Explanatory Model……...……66
4.2.1 Hypothesis I……67
4.2.2 Hypothesis II…….……..67
4.2.3 Hypothesis III……..68
4.2.3.1 Non-Dual Beneficiaries……68
4.2.3.2 Dual Beneficiaries…….……68
5 Results and Discussion……70
5.1 Predictive Model Results……70
5.1.1 Non-Dual Beneficiaries……..…….……70
5.1.1.1 Retinopathy…….…...…71
5.1.1.2 Nephropathy……..……71
5.1.1.3 Neuropathy……72
5.1.2 Dual Beneficiaries……..…….……73
5.1.2.1 Retinopathy……...……73
5.1.2.2 Nephropathy…….…….……74
5.1.2.3 Neuropathy……75
5.1.3 Individual Risk Profiles…….…….…75
5.2 Explanatory Model Results……..…77
5.2.1 Hypothesis I……79
5.2.1.1 Non-Dual Beneficiaries……79
5.2.1.2 Dual Beneficiaries……...……..81
5.2.2 Hypothesis II…….…..83
5.2.2.1 Non-Dual Beneficiaries……83
5.2.2.2 Dual Beneficiaries……...……..85

5.2.3 Hypothesis III……..86
5.2.3.1 Non-Dual Beneficiaries……86
5.2.3.2 Dual Beneficiaries……88
5.3 Model Performance……89
6 Conclusion……94
References……99
Appendix A……104
Appendix B……105
Appendix C……107
Appendix D……109
Appendix E……111
Appendix F……120

List of Tables

Table 1. Claim files utilization summaries by each component, in the year 2010……21

Table 2. Total unique beneficiaries in master beneficiary files, in 2010 and 2011……...22

Table 3. Frequency distribution of Age_group variable, for non-dual and dual beneficiaries……...33

Table 4. Frequency distribution of Age_grp variable, for non-dual and dual beneficiaries……...34

Table 5. Frequency distribution of Sex variable, for non-dual and dual beneficiaries…..34

Table 6. Frequency distribution of Race variable, for non-dual and dual beneficiaries…35

Table 7. Frequency distribution of Race_1 variable, for non-dual and dual beneficiaries…..…….35

Table 8. Frequency distribution of total comorbidity, for non-dual and dual beneficiaries……...37

Table 9. Summary measures of Los variable, for non-dual and dual beneficiaries……...39

Table 10. Summary measures of Los_1 variable, for non-dual and dual beneficiaries….39

Table 11. Summary measures for inpatient and outpatient admissions and office visits, for non-dual and dual beneficiaries…….40

Table 12. Frequency distribution of SNF_stay variable, for non-dual and dual beneficiaries……...41

Table 13. Total occurrences of negative costs by cost component, in 2010……..44

Table 14. Summary measures for total cost, for non-dual beneficiaries in 2010……..46

Table 15. Summary measures for total cost, for dual beneficiaries in 2010……..46

Table 16. Physician primary specialty types……..50

Table 17. Frequency distribution of Prmry variable, for non-dual and dual beneficiaries…...……51

Table 18. Frequency distribution of Prmry_p variable, for non-dual and dual beneficiaries...……52

Table 19. Frequency distribution of Urb variable, for non-dual and dual beneficiaries…54

Table 20. Summary measures for patient cost, for non-dual beneficiaries……57

Table 21. State Medicaid Investment by unique beneficiary, in year 2010……...59

Table 22. Frequency distribution of Diabetes complication (retinopathy, nephropathy and neuropathy), for non-dual and dual beneficiaries……..62

Table 23. Odds ratios (with 95% CLs) for retinopathy complication, for non-dual beneficiaries……...71

Table 24. Odds ratios (with 95% CLs) for nephropathy complication, for non-dual beneficiaries……...72

Table 25. Odds ratios (with 95% CLs) for neuropathy complication, for non-dual beneficiaries……...73

Table 26. Odds ratios (with 95% CLs) for retinopathy complication, for dual beneficiaries…...……...…….74

Table 27. Odds ratios (with 95% CLs) for nephropathy complication, for dual beneficiaries……...74

Table 28. Odds ratios (with 95% CLs) for neuropathy complication, for dual beneficiaries……...75

Table 29. Parameter estimate results for hypothesis I (cost_all), for non-dual beneficiaries……...80

Table 30. Parameter estimate results for hypothesis I (cost_all) for non-dual beneficiaries, using HCC and Comorb risk adjustment……...81

Table 31. Parameter estimate results for hypothesis I (cost_all), for dual beneficiaries...82

Table 32. Parameter estimate results for hypothesis I (cost_all) for dual beneficiaries, using HCC and Comorb risk adjustment……...83

Table 33. Parameter estimate results for hypothesis II (prmry_p and urb), for non-dual beneficiaries……...85

Table 34. Parameter estimate results for hypothesis II (prmry_p and urb), for dual beneficiaries……...…86

Table 35. Parameter estimate results for hypothesis III (cost_all_p), for non-dual beneficiaries……...87

Table 36. Parameter estimate results for hypothesis III (cost_all_p) for non-dual beneficiaries, using HCC and Comorb risk adjustment…….88

Table 37. Parameter estimate results for hypothesis II (mcaid_all), for dual beneficiaries……...89

Table 38. C-statistic performance results for predictive and explanatory models in study……...90

List of Figures

Figure 1. Sample selection process to obtain data sets for non-dual and dual beneficiaries……...26

Figure 2. Complication rate by risk profile, for non-dual beneficiaries…….…..76

Figure 3. Complication rate by risk profile, for non-dual beneficiaries……...77

Figure 4. Distribution of predicted outcome for nephropathy (y_pred) stratified by actual outcome (y=0 or 1), for dual beneficiaries (Hypothesis II)…….…..91

Figure 5. Distribution of predicted outcome for nephropathy (y_pred_spline) stratified by actual outcome (y=0 or 1), for dual beneficiaries (Hypothesis II)…….....93

Chapter 1 Introduction

This dissertation will focus on the roles that the provider, treatment and patient play in development of complications in Diabetes patients. In particular, the dissertation will explore the answers to the following questions:

Do different providers use different treatments on a cohort of Diabetes patients, and are their outcomes different? Also, do different patients play a role in different outcomes, for a given provider and treatment regimen?

This dissertation will explore these types of questions with the hope of offering some background into what factors may be playing a role in the development of complications in Diabetes patients, and ultimately to finding approaches to prevention of these complications.

1.1 Study Description

This dissertation will be exploring the factors that impact the development of Diabetes complications (retinopathy, nephropathy and neuropathy) in Medicare and dual eligible beneficiaries. The study design will be based on two years of data, from 2010 (base year) to 2011 (follow-up year). In 2010, patients are chosen who have Diabetes but who have no complications. In other words, the patients chosen are non-complicated Diabetes patients. Then in 2011, the complications rates for those patients are measured to see which of these patients develop any of the three complications of interest in this study- retinopathy, nephropathy or neuropathy.

One of the unique aspects of this study is the selection of a set of patients without any Diabetes complications. Thus in the base year, a clean sample of Diabetes patients is selected in the sense of having patients with no previous record of any complications. These patients are then observed for development of complications in the follow-up year. The selection of a pure sample of Diabetes patients having no complications in their background allows for a study design that attributes as much as possible the effect of those factors on the development of Diabetes complications in patients. In other words, the effect of the development of complications in Diabetes patients is isolated as much as possible in this study design by selecting a clean sample approach. Although this is an observational study design, it creates a framework to attribute as much of the impact as possible to the various factors on development of Diabetes complications.

In addition to selecting a clean sample of Diabetes patients without having had any complications, another unique aspect of this study is in its extensive focus on risk adjustment. Once the factors have been isolated with regards to their impact on complications development in patients, it is then necessary to apply risk adjustment to make a comparison between similar risk groups. It is not sufficient to simply compare impact of factors on complications development, but it is also important that those impacts are adjusted based on risk levels. Risk adjustment allows for comparison of similar risk category of patients.

To study the exploration of the factors that impact development of Diabetes complications in patients, the overall study will be divided into two parts.

In the first part, predictive models are obtained to study the impact of risk factors on development of Diabetes complications in patients. In this part, only demographic comorbidity and health utilization risk factors are considered in their impact on Diabetes complications development. These factors represent patients' health risk status. These factors are considered non-controllable risk factors due to the fact that a patient does not have control to change those factors' status. For instance, health comorbidities for a patient are typically not within the patient's control to alter. These factors are present in patients and there are usually no options to alter those factors in a patient. These factors are medical risk factors that generally cannot be altered in patients and impact their development of Diabetes complications.

In this stage, predictive models will be used to study the impact that those non-controllable risk factors in patients have on the development of Diabetes complications in those patients in the follow-up year. The results of the predictive models allow the identification of beneficiaries at risk of developing Diabetes complications. It is the purpose of the second stage (and the main purpose of this dissertation) to identify ways to control the rate of development of Diabetes complications for those beneficiaries at risk.

In the second stage, controllable risk factors of patients are studied for their impact on development of Diabetes complications. In contrast to the non-controllable risk factors in

the first stage, these factors are controllable in that they can in general be altered for a given patient. For example, the type of treatment a patient received, or the amount of treatment spending given for a patient. In a sense, those are social risk factors, in contrast to the medical risk factors considered in the first stage.

The controllable risk factors that are explored in this study will include: 1) total cost of treatment 2) physician attributes (primary vs. specialty and urban vs. rural) and 3) patient cost sharing (or Medicaid cost per beneficiary in the case of dual eligible patients). Explanatory models will be developed to evaluate the impact of each of those factors on their impacts on the development of Diabetes complications in Medicare and dual eligible patients.

There will be three hypothesis that will be explored for each of those factors and their impact on Diabetes complications in the second stage. The following gives an overview of the hypotheses that are explored in this study:

1. Higher treatment investment is associated with lower rates of complications in Diabetes patients
2. Provider type plays a role in development of complications in Diabetes patients
    a. Specialist providers have lower rates of complications than generalist providers in Diabetes patients
    b. Urban providers have lower rates of complications than rural providers in Diabetes patients

3. Patients with higher cost-sharing (or higher Medicaid cost per beneficiary for dual eligible beneficiaries) have lower rates of Diabetes complications

1.2 Specific Aims, Including Statement of Hypothesis

The aim of this dissertation is to study factors that influence progression of complications in Diabetes patients. There will be three factors that will be explored for their influence in development of complications in Diabetes patients: the provider, the patient and the treatment investment. These three factors will form the core of the three hypotheses of this dissertation, and each will be explored in more depth in the dissertation. The following are the three hypothesis, along with the types of questions each will attempt to answer:

1. Do different treatment investment levels influence the development of complications in Diabetes patients, for given provider type?
    a. Is higher treatment investment associated with lower rates of complications in Diabetes patients?
    b. Treatment investment consist of costs associated with inpatient, outpatient, professional and other related expenses, for both Diabetes and comorbidities.
2. Do provider types play a role in development of complications in Diabetes patients, for given treatment cost level? Three different provider types will be explored.

    a. Generalist vs. Specialist-Do specialist provider deliver superior care and have lower rates of complications in their Diabetes patients?
    b. Urban vs. Rural-Do urban providers have lower rates of complications in their Diabetes patients?

3. Does patient insurance cost sharing level play a role in development of complication in Diabetes patients, for given provider type and treatment cost level? This hypothesis will examine two areas:
    a. Do patients with higher deductible (or coinsurance) take more active role in their Diabetes self-management and show lower rates of complications development?
    b. For patients who are dual eligible, does state per beneficiary investment in Medicaid influence the rate of complications development in Diabetes patients of that state?

It is hoped that by answering the above questions relating to each hypothesis, that more insight is gained into the factors that influence progression of complications in Diabetes patients. These types of factors play a role in the overall care provided for Diabetes patients. The insight gained from learning about these factors will enable a Diabetes delivery of care model that most effectively considers the role of provider, patient and treatment leading to outcomes with lower rates of complications for Diabetes patients.

Chapter 2 Literature Review

2.1 Diabetes

Diabetes is a leading chronic condition, affecting over 25 million people in the US (or 8.3% of the US population) [1]. Approximately 19 million of those are diagnosed, with another 7 million undiagnosed. The trends show that the prevalence of Diabetes has been increasing and expected to continue rising in the future, especially in light of our growing obesity trends [2]. Diabetes is the 7th leading cause of death in the US [1]. It is clear that Diabetes is a growing concern and becoming an epidemic for our country with trends growing at an alarming rate. By 2030, 36 million people are expected to $_{be}$ diagnosed with Diabetes and 48 million by 2050 [3].

Diabetes is also a very costly chronic condition. According to the American Diabetes association, the total costs of Diabetes in the US is estimated to be $245 billion in 2012. This is a 41% increase from the 2007 estimate, where it was at $174 billion. Of that amount, $176 billion is attributed to direct medical costs (the remaining to indirect costs, or cost due to lost productivity). People with Diabetes typically cost on average 2.3 times more than those without

Diabetes [4]. Further, people with Diabetes have 2 times higher risk of death than people without Diabetes (and with similar age) [1]. The trends for future costs are increasing at a fast rate and expected to at least double in the next 25 years (from 2009) [5].

An estimated 26.9% of Medicare beneficiaries have diabetes, or 10.9 million of the US population [1]. According to the CMS, 32% of total Medicare spending accounts for Diabetes spending (or 1 in 3 dollars). Medicare dual eligibles are beneficiaries who qualify for both Medicare and Medicaid, generally due to their financial hardship. There are nearly 9 million total dual eligibles (about 2/3 are low income and >65) [6]. Dual eligibles per beneficiary costs are more than 4 times the per beneficiary costs of Medicare beneficiaries [6]. This dissertation will focus only on Medicare and dual eligible beneficiaries in the study of factors that influence development of Diabetes complications.

2.2 Diabetes Complications

Complications resulting from Diabetes make up a significant portion of the total cost spent on Diabetes [7]. Overall, cost associated with complications make up about 50% of Diabetes total (direct) cost. In 2007, Diabetes cost was estimated at $174 billion, and $116 billion was attributed to direct medical costs. Of that amount, $27 billion (23.3%) was spent to treat diabetes, $58 billion (50%) to treat Diabetes complications and the remaining (26.7%) was excess general medical cost [4]. Lifetime costs attributed to Diabetes complications are estimated at $47,240 per patient over a 30 years period [8]. In a similar study, age-gender weighted average of the lifetime medical costs for Diabetes patients was estimated at $85,200, of which 53% was spent on treating Diabetes complications [9].

Diabetes complications are usually classified as either microvascular or macrovascular. Microvascular complications usually include retinopathy (eye disease), nephropathy (kidney disease) and neuropathy (nerve disease, attributed to foot amputations in Diabetes patients) [7]. Macrovascular complications usually include complications such as stroke and heart disease [7]. Macrovascular complications comprise the biggest portion of total Diabetes costs-up to 85% in the first 5 years [9]. Another study found macrovascular complications to account for 57% of lifetime Diabetes costs [8]. Additionally, in that study, complications types as a percentage of costs over a 30 year time period had the following percentage breakdown: macrovascular (52%), nephropathy (21%), neuropathy (17%) and retinopathy (10%).

Microvascular complications are a significant burden on the health of Diabetes patients. According to the CDC, retinopathy is the leading cause of blindness in the US among adults 20-74 years. Also, 44% of all new cases of kidney failure in 2008 are attributed to diabetes. Finally, 60% of nontraumatic lower-limb amputations are attributed to patients with Diabetes [1]. It is evident that microvascular complications have a significant impact on the health of Diabetes patients. This dissertation will be focusing predominantly on microvascular complications in Diabetes patients.

2.3 Diabetes Comorbidities

Although Diabetes complications are a costly component of total amount spent on diabetes, costs are more significant in Diabetes patients who have been diagnosed with a

comorbidity. Only 14% of Diabetes are reported to having no comorbidities [10]. In general, Diabetes costs are underestimated when comorbidities are not considered, as was found in a Swedish study where Diabetes costs were 2.5 times higher than earlier estimated when comorbidities were considered [11]. Health utilization in Diabetes patients is increased as a result of having comorbidities. Having both Diabetes and non-Diabetes related comorbidities were both found to have an impact on health utilization, with certain comorbidities having greater impacts [12]. Also, vascular and non-vascular (i.e., non-Diabetes related) comorbidities were found to be equally important in their effects on health utilization in Diabetes [12].

In general, having more than one comorbidity leads to an increase of health utilization and costs in Diabetes patients. A higher number of comorbidities is related with increasing health utilization in patients [12]. A comparison of pairwise combinations of three comorbidities in Diabetes patients showed an increase in costs compared to patients having only one of the comorbidities, and patients having all three comorbidities showed the highest costs [13].

Hypertension is a common comorbidity in Diabetes patients [10]. Patients with both Diabetes and hypertension comorbidities would benefit from better adherence to drug regimen [14]. Depression is also a frequent comorbidity in Diabetes patients [7]. Having depression in Diabetes patients (both minor and major) is associated with increased mortality [15]. Further, it has been found that Diabetes can be a predictor of depression in some patients-it can double the odds of comorbid depression [16]. Obesity, is also a

common comorbidity among Diabetes patients [10], and is associated with an increase in total Diabetes costs [17]. Cardiovascular disease is one of the most significant comorbidities for patients with Diabetes [7]. Diabetes patients with comorbid cardiovascular diseases experience increased hospital expenditures [18]. Nephropathy, as a comorbidity in Diabetes patients, is associated with increases in higher medical care costs in Diabetes patients who are also hypertensive [19].

2.4 Prevention of Complications

As a result of the detrimental effects of diabetes, both in terms of cost and health, it is desirable to practice prevention. Prevention should first and foremost be focused on avoidance of getting Diabetes in the first place. There are a number of ways persons at risk should consider in order to avoid developing diabetes, which generally include eating healthy and remaining active [20].

If a person has already been diagnosed with diabetes, then prevention should turn its focus on avoidance of complications associated with the disease as much as possible. This dissertation will be focused on this case, with Diabetes patients who have no complications (as defined in our study) but who are at risk of developing Diabetes complications. It is believed that there is a difference between those patients with Diabetes who have developed complications and those who have not. Patients with Diabetes who have not yet developed a complication should focus on maintaining that state as long as possible.

Even if a Diabetes patient has developed a complication, it may be worthwhile to avoid developing further complications. Hence prevention must continue to be observed even after development of a complication has occurred in a Diabetes patient [21].

Prevention of Diabetes complications is typically accomplished by controlling clinical factors in Diabetes patients[1]. These clinical factors include glycemic (glucose) and non-glycemic factors including blood pressure, cholesterol levels and body weight [22]. Generally, glycemic control and blood pressure are effective in prevention against microvascular complications. Non-glycemic control factors including blood pressure and lipids are generally effective in prevention against macrovascular complications [7]. There are numerous studies that show the benefit of both glycemic and non-glycemic control in the prevention of Diabetes complications, both interventional and observational.

Two well-known interventional studies took place that established the benefit of glycemic and other clinical factors in the prevention of Diabetes complications. The DCCT study, which occurred in the US from 1983-1993, showed that glycemic control does have an impact on the prevention of complications in Diabetes I patients (also applicable to Diabetes 2 patients [23]) [24]. The UKPDS was a seminal study that took place in the UK from 1977-1997. The UKPDS showed the benefit of controlling

[1] This could be achieved in a number of ways, typically with the use of medications or other regimen proposed by the physician

glycemic clinical factors and the impact on prevention of complications (both microvascular and macrovascular) in Diabetes patients [25].

Raised blood pressure was found to raise the risk of Diabetes complications using UKPDS patients, both for microvascular and macrovascular complications [26]. Also in UKPDS patients, an association between glycaemia and both microvascular and macrovascular complications in Diabetes was determined [27].

Numerous observational studies also highlighted the impact of controlling various clinical factors in the prevention of complications in Diabetes patients. Controlling for glucose and blood pressure were shown to have an impact on microvascular complications (nephropathy and retinopathy), and blood pressure an impact on macrovascular complications (cardiovascular and stroke) in Diabetes patients [28]. Glycemic control demonstrated a reduced risk of additional complications in Diabetes patients who already had one complication [21]. In a study involving both commercial and Medicare patients, it was found that control of A1c, blood pressure and lipids lead to improved probabilities of complications (using probabilities based on UKPDS risk model) as well as improvements in cost [29]. Finally, Diabetes patients with metabolic syndrome (as defined by AHA/NHLBI and IDF criteria) are at greater risk in the development of all Diabetes complications [30].

The benefits of glycemic control are more effective if administered to patients with early onset of diabetes. In a study that used Markov models to quantify the benefits of

glycemic control (in the prevention of both blindness and end-stage renal disease in Diabetes patient), substantial benefit was achieved from almost-normal glycemic control in prevention of complications [31]. For Diabetes patients with later onset, the study found moderate glycemic control was effective in the prevention of most end-stage microvascular Diabetes complications. The benefits of beginning early treatment for Diabetes patients is significant. Glycemic control is more effective when given early to Diabetes patients and in some cases may help prevent long-term macrovascular complications when given at early stages of the disease in some patients [32].

For Diabetes patients who have comorbidities glycemic control can be a challenge and is not always easy to measure. In patients with severe nephropathy, assessing glycemic control is a challenge and accuracy of glucose assays (used for glycemic control) for those patients is affected [33].

This dissertation considers a broader approach to the prevention of complications in Diabetes patients than the current focus on glycemic and other clinical factors. The approach in this dissertation is a multi-fold approach that considers the role of the provider, the patient and treatment type and their impact in the development of complications in Diabetes patients. This approach is more comprehensive in the treatment of complications in Diabetes patients than simply focusing on controlling glycemic and nonglycemic factors. Fitch et al. discuss the benefits of treatment of Diabetes that goes beyond clinical factors [29]. Their discussion focuses on both provider and patient programs that have the potential to provide more effective care

programs for Diabetes patients. With innovative provider and patient programs, more patients would receive Diabetes preventive care at more appropriate times, leading to better outcomes. Krein et al. offer suggestions to Diabetes care management that will lead to improved economic outcomes [34]. The topics discussed include improved patient cost sharing programs, more effective insurance designs and provider programs that are aimed at quality improvement. This dissertation's goals are to explore the impact of these types of innovative approaches and the role they have in prevention of complications in Diabetes patients. The three areas explored will include treatment investment, provider type and patient cost sharing in the management and prevention of Diabetes complications.

2.4.1 Treatment Investment

First, the amount of treatment investment[2] will be explored. In this dissertation, the amount invested in treatment of Diabetes will be used as a proxy for treatment type, as this captures both the treatment intensity and the quality of the treatment provided. In general, treatment investment increases after Diabetes complications take place in Diabetes patients. Patients who had better control of glycemic, blood pressure and lipid factors demonstrated cost savings, in both commercially insured and Medicare patients [29]. Patients with maintained good glycemic control (at or below A1c levels of 7%) had lower diabetes-related cost than Diabetes patients who did not [35]. However, it is of

[2] Treatment investment refers to all expenses resulting from inpatient, outpatient, physician office, skilled nursing facility or home health

interest to study the role treatment investment plays in Diabetes patients who have not yet developed complications, and this will be explored in this dissertation.

In addition, certain patients may require specialized treatment for their condition, sometimes requiring administration of treatment at early stages of Diabetes (before symptoms may arise) [32]. These types of patients would require higher levels of treatment investments. It is the goal of this dissertation to evaluate the role of treatment investment as a way to capture the impact that various treatments have on the developments of complications in Diabetes patients.

2.4.2 Provider Type

This dissertation will also evaluate the impact that providers play in the development of complications in Diabetes patients. Two different components of provider type will be explored. First the difference between generalist vs. specialist providers will be considered. In general it is believed that specialist providers provide better care for Diabetes patients, especially in terms of complications development [36-38]. However, it has also been found that treatment of Diabetes patients with both a generalist and an endocrinologist provides for best outcomes [39]. In the second area, rural vs. urban providers will be considered. Many studies have examined the impact of rural vs. urban provider in the treatment of diabetes, and generally it is believed that urban providers deliver better care [40-43].

2.4.3 Patient Cost Sharing

The last focus of this dissertation will be on the role the patient in the management of Diabetes and in the prevention of complications. In recent years, there has been an increased interest in involving the patient in the treatment of Diabetes (and other chronic diseases in general). This dissertation will study the impact that insurance plays in providing the patient incentives to be active in the management of their Diabetes disease. Diabetes in particular is a disease that requires active involvement of the patient in management of their treatment [44]. This study will explore the impact that patients' cost sharing has on developments of complications in Diabetes patients. There is conflicting evidence about patient cost sharing's relation to health outcomes. Increase in patient cost share has been shown to have an adverse effect on health utilization, and particularly in diabetes preventive services [45]. On the other hand, there improved health utilization has been observed in consumer driven health plans (CDHP) that offer patients high deductible cost sharing [46-48]

One extension to patient insurance will be to evaluate the dual eligible patients separately. Dual eligible patients do not have any cost sharing, as they are covered by Medicaid in addition to their Medicare coverage. In this extension the study will explore the impact that states' per beneficiary investment in Medicaid has on the outcome of Diabetes dual eligible patients and their development of complications.

2.5 Study Design

The study design in this dissertation will consider patients without any Diabetes complications and examine the impact that various factors have on whether they develop Diabetes complications in the following year. Also, risk adjustment will play a pivotal role, in order to ensure that there is a level comparison between various patient risk groups. To some extent, there have been some similar such study designs for various different disease conditions. For instance, Menzin et al. consider a multivariate logistic regression model to study the impact that mean A1c levels of patients had on Diabetes related hospital inpatient admission [49]. In that study, mean A1c is divided into five distinct levels (from <7% to 10% and more). The impact of mean A1c on patient hospitalization was risk adjusted for a number of risk related covariates, including age, sex, number of A1c test, diagnosis of cancer and follow-up time.

In Wagner et al used linear regression with risk adjustment to evaluate the impact that HbA1c control had on both cost and utilization intensity of patient [50]. Utilization intensity included % admission to hospital, mean total visits to primary care and mean total visits to specialist visits. Patients were divided into two groups, those whose HbA1c levels improved and those that did not improve. Thus there are two levels for comparisons in this case. Risk adjustment factors included age, sex, baseline HbA1c level and baseline presence of any of six Diabetes complications.

Bertoni et al. considered patients who did not have prevalence of heart failure in the base year (1994) and evaluated incident heart failure in the follow-up period (1995-99) for

those patients [51]. Proportional hazard regression was used to evaluate the risk of incident heart failure among the cohort, with risk adjustment of covariates including age, sex, race and Diabetes related comorbidities. The study population was Medicare beneficiaries who are older (>= 65 years) and not in managed care, similar to the population in this dissertation.

2.5.1 Prediction

In addition to studying the impact of analytical factors on disease outcomes, risk adjusting for risk factors, another approach is prediction of disease prevalence based on risk factors. This dissertation will explore prediction of Diabetes complications among Medicare and dual eligible beneficiaries based on a variety of socio-demographic and health related risk comorbidities.

There are a number of studies related to predictive modeling of patient disease risk based on a variety of risk factors, including patient disease history. Many of these recent studies are employing more cutting edge analytics in their modeling using claims based data sets. Davis et al. explored prediction of individual disease risk based on a patient's medical history (using ICD-9 diagnosis codes) [52]. Although the data requirement is fairly straightforward in Davis et al. (using only claims based data), the approach is fairly sophisticated. Collaborative filtering combined with clustering is used to discover disease risk for patient based on disease diagnosis in prior visits. This approach shows improvements in prediction based on more number of visits by the patient.

Khalilia et al. is also an innovative approach to prediction of disease based on patient diagnosis history, using the National Inpatient Sample Data [53]. Random forests are used for prediction of eight diseases. To deal with the highly imbalanced nature of the data, ensemble learning approach based on repeated random sub-sampling is used. The results based on random forest ensemble learning prediction are shown to outperform other prediction approaches (including support vector machine (SVM), bagging and boosting). Moturu et al. also tackle the imbalanced data issue in their Medicaid cost prediction study, using claims based data (the Arizona Health Care Cost Containment System) [54]. Although this study is concerned with cost prediction, the classes of cost can be viewed as a proxy for patient risk (i.e., disease risk). Moturu et al. apply non-random sampling (under-sampling and over-sampling) to deal with the data imbalance problem and apply several predictive modeling methods including SVM, logistic regression and logistic model trees.

Yu et al. apply SVM for prediction of common diseases, for both Diabetes and pre-Diabetes [55]. The data set was based on the National Health and Nutrition Examination Survey, and only included common clinical measurement (without more sophisticated laboratory tests). The results of the prediction based on SVM were shown to be equivalent to the more mainstream multivariate logistic regression that is more commonly used in these studies. The advantages of using SVM is it does not require any distributional assumptions and this becomes valuable as more variables are introduced in

the model. Robinson explores using boosted regression trees with simple claims data and shows the advantages in consideration of all variable interactions with this approach [56].

Chapter 3 Methods

3.1 Data Source

The population that will be studied in this dissertation will be Medicare beneficiaries (including dual eligible beneficiaries). The data source will be based on Medicare Limited Data Set (LDS) from 2010-2011. This data set contains both institutional and non-institutional claim files for a 5% sample of Medicare Beneficiaries. Both Medicare Parts A and B are included in the data set. A very thorough introduction on the use of the Medicare Limited Data Set is provided in Parente et al [57].

Within the Medicare LDS data set, five distinct files are investigated for beneficiary claim utilization. These claim utilization files consist of: 1) Carrier 2) Outpatient (OP) 3) Inpatient (IP) 4) Skilled Nursing Facility (SNF) and 5) Home Health (HHA) files. The following table shows summary results for each of those five claim files for the year 2010 (the base year), including results for total unique claims, total costs (claim payment made) and total unique beneficiaries.

	Total Claims	**Total Costs**	**Total Beneficiaries**
Carrier	43,075,835	$4,278,138,670.80	1,711,151
Outpatient	7,432,322	$2,696,479,024.90	1,210,151
Inpatient	622,201	$6,284,780,092.40	356,405
SNF	281,601	$1,366,641,320.10	96,850
HHA	350,082	$1,133,951,371.10	173,154

Table 1: Claim files utilization summaries by each component, in the year 2010

In addition to the claim utilization data files, a master beneficiary file (or denominator file) is also included as a data source. The master beneficiary file is also part of the LDS Medicare data set and contains detailed information about beneficiaries enrolled in Medicare. For instance, some of the information included consists of demographics (age/sex/race), original (and current) reason for enrollment of a beneficiary in Medicare, enrollment in Part A or B (or both), and more. The following table shows the total unique beneficiaries included in the 2010 and 2011 master beneficiary files that are used in this study. Note that in 2011, the total includes all of the Medicare population (instead of a 5% sample, as is the case in the Medicare LDS data set in general). However, this study will only consider a 5% sample which will be restricted based on the 2010 beneficiary data.

	Year 1 (2010)	**Year 2 (2011)**
Total Beneficiaries	2,499,647	51,548,729

Table 2: Total unique beneficiaries in master beneficiary files, in 2010 and 2011

For Medicare beneficiaries who are dual eligible, additional data for State Medicaid per beneficiary investment will be needed. The data source for State Medicaid per beneficiary investment will be obtained from the CMS Medicaid Statistical Information System (MSIS) State Summary Datamart. This database contains Medicaid spending

data by state for years prior to 2012, which is the case for this study (where data for the year 2010 will be obtained)[3].

3.2 Data Collection

Using the data sources as presented above, the study will be focused on investigating the impact of factors that influence the development of Diabetes complications in Medicare and dual eligible patients. The data collection process will proceed in the following two phases. In the first phase, data for a beneficiary is collected during the base year (2010). In the second data collection phase, data for a beneficiary is obtained during the follow-up year (2011). The following provides an overview of the data collection process in the dissertation:

A. Phase I:

Patients are chosen in year 1 (2010) who meet the following criteria:

1. Have at least 1 Diabetes diagnosis in that year
2. Have no observed diabetes complications

For each beneficiary, the following information is collected in the base year:

1. Socio-demographic (age, sex, race)
2. Health utilization factors
3. Patient co-morbidities

[3] The CMS MSIS data is located at http://www.cms.gov/Research-Statistics-Data-and-Systems/Computer-Data-and-Systems/MedicaidDataSourcesGenInfo/MSIS-Mart-Home.html

4. Analytical factors-Total cost of treatment, MD factors and patient cost sharing/Medicaid state per beneficiary investment (for dual eligible beneficiaries)

B. Phase 2:

In year 2 (2011), patients will be observed for the complications that they develop.

1. They must have at least 1 Diabetes diagnosis in that year
2. Deceased patients are not included in study

3.3 Sample Selection

The sample selection process in this dissertation is shown in Figure 1. The following describes the steps in the sample selection process in Figure 1 in more detail. First, patients are chosen in 2010 based on having a Diabetes diagnosis. In this study, Diabetes diagnosis is defined as having an ICD-9[4] diagnosis code of 250.xx [49]. Each of the five claim utilization source files are used to determine a Diabetes diagnosis for a beneficiary: carrier, IP, OP, SNF and HHA. For carrier and OP source files, at least two occurrences of ICD-9 code 250.xx are used to define a patient as having Diabetes. All other source files (IP, SNF and HHA) only require at least one such occurrence of ICD-9 code 250.xx. The reason for this distinction is that both the carrier and OP claim files are much larger sources of claim utilization than IP, SNF or HHA. This stricter guideline for carrier and OP claim files minimizes the potential for error in identification of Diabetes patients from those two sources [58, 59]. For all the claim utilization source files, a patient's primary

[4] International Classification of Diseases, Ninth Revision (ICD-9)

diagnosis and an additional five diagnosis codes are used in order to identify a patient as having Diabetes diagnosis[5].

The total number of beneficiaries that are obtained after considering all five claim utilization sources for occurrence of Diabetes diagnosis in 2010 results in a total of 423,957 beneficiaries (see Figure 1)[6].

In addition to the restrictions above based on the claim utilization source files, additional restrictions are also made that are based on the master beneficiary tables in both 2010 and 2011. These restrictions are meant to reduce the set of beneficiaries to only those presumed eligible for this study. These restrictions are all based on recommendations obtained from the Research and Data Assistance Center (RESDAC) at the University of Minnesota[7]. The justification provided for these adjustments is that they are necessary in order to obtain a complete data set for beneficiaries who are enrolled in Medicare FFS. If a beneficiary does not meet the restrictions presented, it would mean that there is missing data for that beneficiary during a portion of the year.

[5] Some claims utilization sources have anywhere from 10-25 additional diagnosis codes. Only the first five were considered in this study.
[6] Note that in Figure 1 the numbers represent the final amounts after filtering is done, whereas the discussion highlights the actual amounts filtered in each case (offering a different perspective).
[7] http://www.resdac.org/

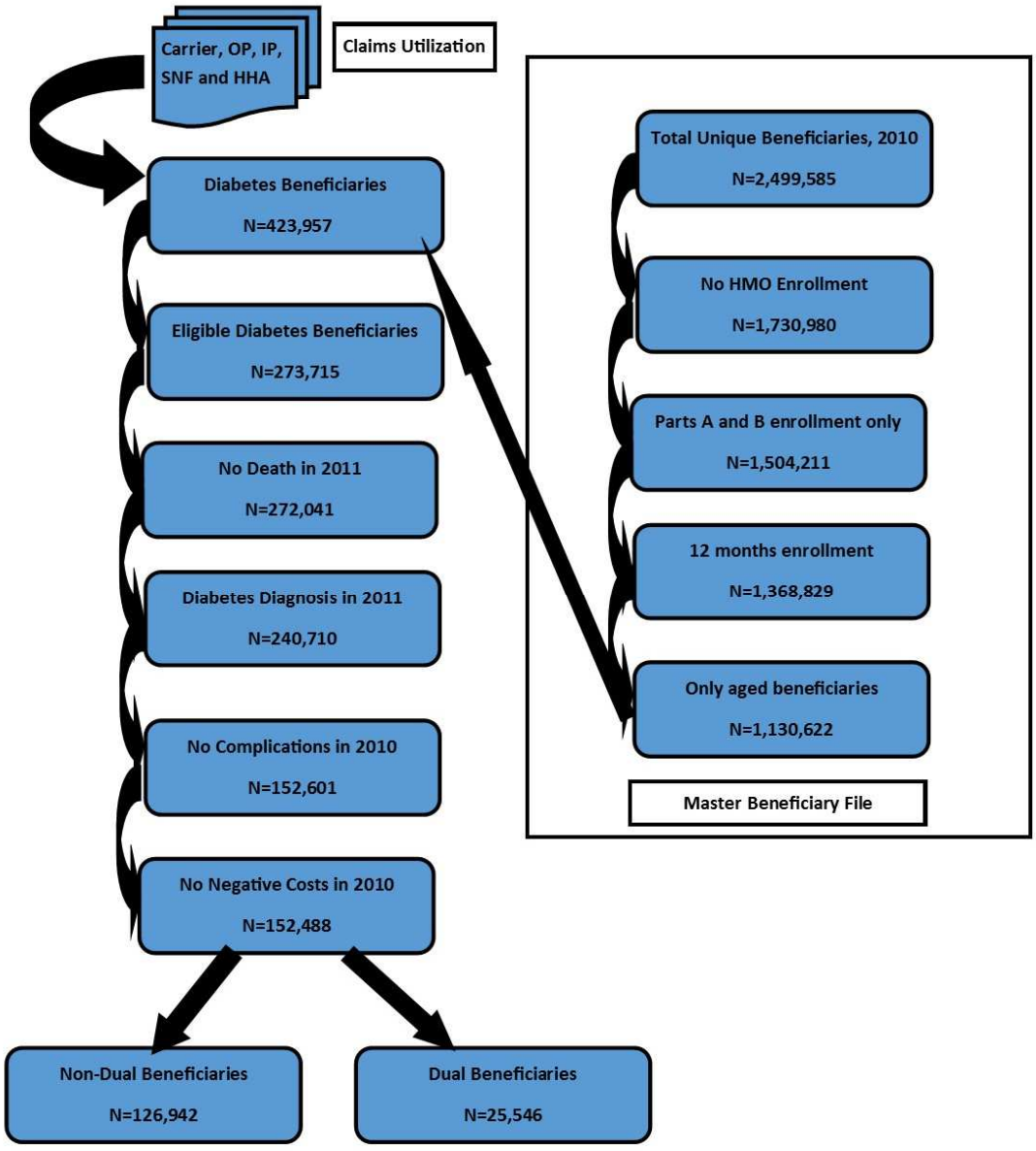

Figure 1: Sample selection process to obtain data sets for non-dual and dual beneficiaries

Before using either of the master beneficiary tables in 2010 and 2011 in the study, they are first both scanned for any possible duplicates. In both years, duplicates were found but accounted for less than .01% duplicates in both tables. Those duplicates were removed from both tables. The total beneficiaries in the master beneficiary tables after removing duplicates for both 2010 and 2011 were shown previously in Table 2 above.

The first adjustment made based on the master beneficiary tables is to select only beneficiaries who were not enrolled in HMO Medicare coverage in any of the 12 months during 2010 or 2011. Any beneficiary with a record of at least 1 month enrollment in an HMO type coverage in either 2010 or 2011 would be excluded from the study[8]. A total of 768,605 beneficiaries were found to have at least 1 month of enrollment in an HMO plan and those beneficiaries were excluded from the study.

A second modification is to only select beneficiaries who were enrolled in both Medicare parts A and B during either 2010 or 2011[9]. This refers to a beneficiary being enrolled in both parts A and B in a year, in contrast to being enrolled in only one of those two parts (either in part A or part B but not both). There were a total of 226,769 beneficiaries who did not meet this criteria of having enrollment in both parts A and B together during either 2010 or 2011 and those beneficiaries were removed from the study.

[8] Patients may elect to be enrolled in Medicare Part C or Medicare Advantage and that would qualify them as being HMO beneficiary for that month

[9] Medicare consists of four parts: A, B, C and D. Part A is the hospital component, part B is the physician component. Part C is for Medicare managed care and Part D is for the drug component.

A third modification was to only choose beneficiaries who had a full 12 months enrollment in each year. This limited the total beneficiaries by a total of 135,382 beneficiaries.

The final modification was to select only aged beneficiaries. In Medicare, a beneficiary generally meets enrollment eligibility as a result of being aged (reaching the age of 65). However, being disabled or having ESRD may also make a beneficiary qualified to enroll in Medicare. In this study, only aged beneficiaries are selected[10]. This restriction limited the set of beneficiaries by a total of 238,207 beneficiaries.

The final list of beneficiaries, after considering all the restrictions imposed as outlined above, comes to a total of 1,130,622 beneficiaries. This is down from an original size of 2,499,585 beneficiaries in 2010 (or about 45% of the original size), after removing a total of 1,368,963 beneficiaries that are not considered eligible for this analysis.

After obtaining the reduced set of beneficiaries eligible for this study, the next step is to limit the sample of beneficiaries having Diabetes in 2010 as identified above to only those meeting eligibility criteria as has been identified. The final set of beneficiaries after combining those two results comes to a total of 273,715 beneficiaries. Thus our previous total of 423,957 beneficiaries having Diabetes in 2010 is now reduced to 273,715 beneficiaries (or about 65% of the original size) after considering all the additional beneficiary eligibility modifications that were discussed above. The new updated set of

[10] Beneficiaries who were aged and having ESRD were chosen. However, beneficiaries with only ESRD were not chosen.

Diabetes beneficiaries will now have complete data for the study period, making them suitable for the study.

After obtaining the eligible beneficiaries who have been diagnosed with Diabetes in 2010, additional restrictions are made to this list of beneficiaries. The following two restrictions are both based on events occurring 2011. First, beneficiaries that were deceased in 2011 are removed from the sample. A total of 1,674 beneficiaries in our sample of 273,715 beneficiaries diagnosed with Diabetes in 2010 were deceased in 2011. These beneficiaries were removed from the sample and the new sample now consists of 272,041 beneficiaries. This list of beneficiaries have complete data in 2011 which will be suitable for this study[11].

A second restriction is made to select only those beneficiaries who have also been diagnosed with Diabetes in 2011. A similar process is followed in 2011 as was done in 2010 above to identify a beneficiary who is diagnosed with Diabetes in 2011. Beneficiaries are selected based on having at least one occurrence of Diabetes diagnosis during that year (or at least 2 occurrences in the case of carrier and OP claim files as was done previously). In addition, only the primary diagnosis and five additional diagnosis codes are evaluated for presence of ICD-9 code 250.xx. After evaluating the list of 272,041 beneficiaries diagnosed with Diabetes in 2010, 31,331 of these beneficiaries (or 11.5%) do not have a Diabetes diagnosis in 2011, and those are removed from the sample-resulting in a sample of 240,710 beneficiaries.

[11] There is a concern of a bias due to removing sicker beneficiaries who more likely may die in 2011. One approach is to perform the analysis with and without removing the deceased. Ideally, the impact should not be significant; otherwise, deceased beneficiaries should not be removed and censoring could be considered.

At this point, the sample consists of beneficiaries having been diagnosed with Diabetes in both 2010 and 2011. However, the study also requires that the sample consist of beneficiaries that do not have any of the three Diabetes complications in 2010- retinopathy, nephropathy and neuropathy. The criteria for these three complications is included in Appendix A where each complication is defined by a list of ICD-9 codes. The list of ICD-9 codes is obtained from surveying the literature related to Diabetes complications [14, 49, 60, 61]. In addition to the three complications in this study, beneficiaries are chosen who do not show evidence of any long-term Diabetes complications. Long-term Diabetes complications are defined with ICD-9 code range 250.4x-250.9x. The first three codes in that range are included in the three main complications of this study. Thus the remaining three codes (250.7x-250.9x) are added to the list of codes defined in Appendix A in defining a beneficiary with Diabetes complications in this study.

The process of identifying beneficiaries with Diabetes complications is similar to the identification of beneficiaries who are diagnosed with Diabetes that was done previously. Similar to the Diabetes diagnosis process, each of the five claim utilization sources are utilized in identifying Diabetes complications diagnosis. In the case of OP and carrier claim utilization source files, at least two occurrences of the Diabetes complications codes must be met for a beneficiary to be considered to have a Diabetes complication diagnosis-only one such occurrence is required in the case of the other claim utilization source files (IP, SNF and HHA). Also, in each case only the principal and five additional

diagnosis codes are used to determine Diabetes complications diagnosis, as was done previously.

Once a beneficiary is identified as having any of the Diabetes complications defined above, they are subsequently removed from the study sample. This will result in a sample of beneficiaries for this study who 1) have Diabetes diagnosis in both 2010 and 2011 (as was obtained above) and 2) have no occurrence of long-term Diabetes complications. A total of 88,109 beneficiaries are found to have at least one of the defined long-term Diabetes complications. After removing those beneficiaries from the sample, the total sample size is reduced to a total 152,601 beneficiaries.

One additional data modification to the final data set related to negative costs. This will be outlined in more detail in the next section when discussing the analytic factor of total costs. Essentially, beneficiaries with any cost components that are negative are removed from the final data set. A total of 113 are found with such negative costs (<0.1%) and the final data set is reduced to 152,488 beneficiaries[12].

Finally, the data set is divided into a non-dual and dual Medicare beneficiaries. Dual beneficiaries are defined as those having at least 1 month of state subsidy in the beneficiary file. After making the split, the final non-dual data set has 126,942 beneficiaries and the dual data set has 25,546 beneficiaries. Those are the final data sets that will are used for modeling in the study.

[12] This will be discussed in more detail in the section below related to cost analytical factors.

3.4 Model Design and Variables

As has been discussed, the objective of this study is to consider the role that various factors have on the development of complications in Diabetes patients. Some of those factors have already been presented, including a differentiation that was made between controllable and non-controllable risk factors. This section will highlight in detail all the variables that are used in the model, including the approaches used to derive some of those variables.

The first part will highlight the independent variables in the model. These will include the: 1) socio-demographic variables 2) comorbidity risk factors 3) health utilization variables (hospital inpatient length of stay, inpatient and outpatient total admissions, total office visits and SNF stay) and 4) analytical variables (total cost of treatment, physician factors and patient cost sharing/Medicaid State per Beneficiary investment in the case of dual eligible beneficiaries). The second part will cover the outcome variables in the study, including: 1) retinopathy 2) nephropathy and 3) neuropathy.

3.4.1 Independent Variables

3.4.1.1 Socio-Demographic Variables

3.4.1.1.1 Age

The first socio-demographic variable used in the study is age. Age is initially in the data as a continuous variable representing a person's age in years. The first modification applied to age is to transform it into a discrete variable called Age_group. The following table shows the results of this transformation as well as the frequencies obtained, for dual and non-dual beneficiaries in the year 2010:

		Non-Duals		Duals	
Age	**Age_group**	**Count**	**Percent**	**Count**	**Percent**
64<=age<70	64 to 69	39,415	31.05%	7,566	29.62%
70<=age<75	70 to 74	33,558	26.44%	6,298	24.65%
75<=age<80	75 to 79	25,126	19.79%	5,032	19.70%
80<=age<85	80 to 84	17,412	13.72%	3,777	14.79%
85<=age	85 and over	11,431	9.00%	2,873	11.25%

Table 3: Frequency distribution of Age_group variable, for non-dual and dual beneficiaries

After considering the frequencies of Age_group in Table 3, the last two categories ('80 to 84' and '85 and over') appear less frequent than the rest. It was decided to merge those two groups into one (to be called '80 and over'). This allows a more smooth distribution of the age groups in the new variable. This new variable is called the Age_grp variable and other than the merging of the last two groups, it is identical to Age_group variable. The following table shows the frequencies for Age_grp variable, for dual and non-dual beneficiaries in the year 2010:

	Non-Duals		Duals	
Age_grp	**Count**	**Percent**	**Count**	**Percent**
64 to 69	39,415	31.05%	7,566	29.62%
70 to 74	33,558	26.44%	6,298	24.65%
75 to 79	25,126	19.79%	5,032	19.70%
80 and over	28,843	22.72%	6,650	26.03%

Table 4: Frequency distribution of Age_grp variable, for non-dual and dual beneficiaries

3.4.1.1.2 Sex

The second socio-demographic variable used in this study is sex. The only adjustment made to sex was to change the labeling from '1' and '2' to 'M' and 'F', respectively. The following shows the frequency of sex in the study, for dual and non-dual beneficiaries in the year 2010:

	Non-Duals		Duals	
Sex	**Count**	**Percent**	**Count**	**Percent**
F	65,662	51.73%	18,305	71.66%
M	61,280	48.27%	7,241	28.34%

Table 5: Frequency distribution of Sex variable, for non-dual and dual beneficiaries

3.4.1.1.3 Race

The last socio-demographic variable used in the study is race. Race was adjusted in a similar way to age above, by grouping categories to create a more smooth distribution. The adjustment essentially grouped all the low frequency categories into one (this

included Asian, Hispanic, North American, Other and Unknown)[13]. The new updated variable is called Race_1, with a new category of 'Other' for the grouped categories. The following tables show the distribution of the Race variable (table 6) and Race_1 variable (table 7), for dual and non-dual beneficiaries in the year 2010:

	Non-Duals		Duals	
Race	**Count**	**Percent**	**Count**	**Percent**
Asian	1,312	1.03%	2,426	9.50%
Black	10,311	8.12%	4,685	18.34%
Hispanic	957	0.75%	2,266	8.87%
North American	603	0.48%	305	1.19%
Other	2,163	1.70%	758	2.97%
Unknown	118	0.09%	72	0.28%
White	111,478	87.82%	15,034	58.85%

Table 6: Frequency distribution of Race variable, for non-dual and dual beneficiaries

	Non-Duals		Duals	
Race_1	**Count**	**Percent**	**Count**	**Percent**
Black	10,311	8.12%	4,685	18.34%
Other	5,153	4.06%	5,827	22.81%
White	111,478	87.82%	15,034	58.85%

Table 7: Frequency distribution of Race_1 variable, for non-dual and dual beneficiaries

3.4.1.2 Comorbidity Risk Factors

Comorbidities are used in this study to risk adjust beneficiaries to obtain a relatively uniform population for the analysis[14]. For this study, the primary approach used for risk adjusting comorbidities is with the Elixhauser comorbidity measure. Elixhauser

[13] All of these categories have frequencies less than 2.5%
[14] Comorbidities are also used as predictive factors in the predictive models initially as well.

comorbidity consists of 31 distinct disease categories defined based on ICD-9 codes [62]. In this study, the Elixhauser comorbidity measures are applied to the five sources of claim utilization (Carrier, IP, OP, SNF and HHA), as was done with Diabetes diagnosis above. Also, as was done with Diabetes diagnosis, main claim diagnosis and five additional diagnosis codes are used with the Elixhauser comorbidity measures to identify occurrences of an Elixhauser disease category. However, for Elixhauser comorbidity measures, unlike with Diabetes diagnosis above, all five claim utilization sources are based on only one occurrence of an ICD-9 code to establish presence a disease condition (i.e., Carrier and OP do not require at least 2 occurrences of an ICD-9 code to attribute a condition to a beneficiary).

A total of 31 disease comorbidities are included in Elixhauser measures. However, in this study, the two comorbidity measures that directly relate to Diabetes (for Diabetes non-complicated and Diabetes complicated) are removed from the analysis. This is done due to the fact that these two conditions have already been captured in the analysis, in both the Diabetes and complicated Diabetes diagnosis conditions. The frequency distribution of Elixhauser comorbidities for the remaining 29 variables is shown in Appendix B. These results are shown for both non-dual and dual beneficiaries, in the year 2010.

A summary of total comorbidities by beneficiary is shown in table 8 below, for both non-dual and dual beneficiaries in 2010. This table highlights the fact that most beneficiaries have total comorbidities in the vicinity of three to five (the median total comorbidity for

both non-dual and dual beneficiaries is four). However, beneficiaries with higher comorbidities, even though constitute lower percentage would typically have a higher percentage of the cost. A grouping of beneficiaries by total comorbidity will be considered in the model as way to categorize the risk level of a beneficiary.

	Non-Duals		Duals	
Total Comorbidity	**Count**	**Percent**	**Count**	**Percent**
0	25	0.02%	6	0.02%
1	3,787	2.98%	471	1.84%
2	26,674	21.01%	3,868	15.14%
3	30,405	23.95%	5,052	19.78%
4	23,688	18.66%	4,560	17.85%
5	16,390	12.91%	3,625	14.19%
6	10,550	8.31%	2,718	10.64%
7	6,488	5.11%	1,907	7.46%
8	3,987	3.14%	1,322	5.17%
9	2,308	1.82%	811	3.17%
10+	2,640	2.08%	1,206	4.72%

Table 8: Frequency distribution of total comorbidity, for non-dual and dual beneficiaries

3.4.1.3 Health Utilization Variables

3.4.1.3.1 Inpatient Length of Stay

Length of stay was calculated for each beneficiary based on inpatient stays. This measure was considered as providing valuable information regarding a patient's health status. This would be valuable to use as a risk adjuster, in addition to the Elixhauser comorbidity risk factors above.

The following describes the steps used in this study to calculate each patient's total length of stay, including any assumptions that were made. It should be noted that this calculation only uses inpatient claim utilization as a source (for the year 2010).

Length of stay for a patient was calculated based on the following formula:

Total length of stay (LOS) = sum [(date of discharge – date of admission) + 1]

The following assumptions were used in the calculation above of length of stay. First, for each person, a date of admission was updated with 'Jan 1 2010' if it was found that the date of admission for a patient was prior to 2010. This ensures that length of stay will only go back only as far as Jan 1 2010. This ultimately allows total length of stay for a patient to remain less than or equal to a year.

In addition, the date of discharge for each person where the last occurring stay has a blank is updated with 'Dec 31 2010'. This is done to ensure that no null length of stays are obtained. For each person with at least one record of an inpatient stay, total length of stay should at least be equal or exceed 1 day.

Also, for each occurrence of an inpatient stay, a one is added to the calculation as is shown in the formula above. This is done to ensure that the last day is counted as inclusive in the calculation and considered in the total for that inpatient stay.

Finally, there were some instances of patients having duplicate admission and discharge dates (i.e., having both of these the same). For these patients, only one such occurrence is counted in the total length of stay calculation and the duplicates are not considered.

In the tables below, the summary measures are shown for the final results for length of stay (n, min, max, mean and median). In the first table (table 9), the results are shown only for patients who have an inpatient stay (Los variable). In the second table, length of stay for patients without an inpatient stay is defined to be 0. The results are defined in a new variable called Los_1 and those results are shown in table 10[15].

	Non-Duals	Duals
N	21,892	5,797
Mean	8.28	10.27
Median	5	6
Min	1	1
Max	266	366

Table 9: Summary measures of Los variable, for non-dual and dual beneficiaries

	Non-Duals	Duals
N	126,942	25,546
Mean	1.43	2.33
Median	0	0
Min	0	0
Max	266	366

Table 10: Summary measures of Los_1 variable, for non-dual and dual beneficiaries

3.4.1.3.2 Inpatient and Outpatient Admissions and Total Office Visits

[15] Note that Los_1 also captures if a patient has a hospitalization, since length of stay would be >=1 for that patient.

Other health utilization variables considered in the study include inpatient and outpatient total admissions and total office visits. These totals are for each beneficiary during the year 2010. Table 11 below shows summaries for all three of those measures (n, mean, median, min and max) for non-dual and dual beneficiaries in the year 2010[16].

	Non-Duals			Duals		
	Inpatient	**Outpatient**	**Office Visit**	**Inpatient**	**Outpatient**	**Office Visit**
N	126,942	126,942	126,942	25,546	25,546	25,546
Mean	0.25	4.21	8.88	0.36	5.46	8.18
Median	0	2	7	0	3	6
Min	0	0	0	0	0	0
Max	13	249	170	14	124	112

Table 11: Summary measures for inpatient and outpatient admissions and office visits, for non-dual and dual beneficiaries

3.4.1.3.3 Skilled Nursing Facility Admission

In addition to inpatient and outpatient admissions and office visits, SNF stay was another health utilization variable considered in this study. SNF stay is a binary measure that shows if a beneficiary has had at least one SNF inpatient admission during the year in 2010. For beneficiaries with no SNF stay during the year, a value of zero is assigned. Table 12 below shows the frequency distribution for the SNF stay variable, for both non-dual and dual beneficiaries in 2010. It should be noted that dual eligible beneficiaries are expected to have a significantly higher SNF stay rate than Medicare beneficiaries [6].

[16] As was done with LOS in table 10 above, all measures in table 11 are assigned a value of zero when a beneficiary does not have any utilization for that measure during the year.

This is reflected in Table 12, where the SNF rate of admission is almost twice that for dual eligible than for Medicare beneficiaries.

	Non-Duals		Duals	
SNF_stay	**Count**	**Percent**	**Count**	**Percent**
0	122,451	96.46%	23,522	92.08%
1	4,491	3.54%	2,024	7.92%

Table 12: Frequency distribution of SNF_stay variable, for non-dual and dual beneficiaries

3.4.1.4 Analytical Factors

Analytical factors are associated with each of the different hypotheses presented above. There are a total of three hypotheses and thus three analytical factors in the study. The analytical factors in the study include total cost of treatment, physician factors (specialty/primary and rural/urban) and patient investment (patient cost and Medicaid State per beneficiary investment in the case of dual eligible). Each of these analytical factors are presented here. Note that these analytical factors are only used in the explanatory models and not the base predictive models, as was previously presented. Also, as has already been discussed, these analytical factors are considered controllable risk factors (this is in contrast to the previously discussed variables, which are treated as non-controllable risk factors). The premise is that a health plan has the capability to vary these factors for a desired outcome in the treatment of a patient. It is the intent of this dissertation to find the levels of these analytical factors that yield the best outcomes in patients' progression of Diabetes complications.

3.4.1.4.1 Total Cost of Treatment

Note: The discussion in this section is also applicable to patient cost sharing, which will be discussed below as part of the third analytical factor.

Total cost of treatment includes all costs incurred by Medicare in treating the patient. These costs are incurred in the base year (2010). The idea behind total cost of treatment is that it is a proxy for the quality of care given to a patient. The combination of all costs incurred in treating the patient during the year present a picture of the level of care that a patient received during the year. These costs consist of all components of care provided. These components are obtained from five different claim utilization sources: Carrier, IP, OP, SNF and HHA.

The following presents the calculation used to obtain total cost of care for each of these five sources[17]. The final amount for total cost of treatment is then obtained as the sum of the total cost of treatment of each of those five components.

i. Carrier

$TC_{Carrier}$[18] =

Sum (Claim payment amount)

ii. IP

[17] All of these calculations are obtained from RESDAC, from workshop presentation 'Intro to Economic Research' (www.resdac.org)
[18] TC stands for Total Cost

TC_{IP} =

Sum (Claim Payment Amount + (Claim Pass Thru Per Diem Amount * Claim Utilization Day Count))

iii. OP

TC_{OP} =

Sum (Claim payment amount)

iv. SNF (same as IP)

TC_{SNF} =

Sum (Claim Payment Amount + (Claim Pass Thru Per Diem Amount * Claim Utilization Day Count))

v. HHA

TC_{HHA} =

Sum (Claim payment amount)

Total cost of treatment is then calculated as the sum of each of the above components, as shown in the following formula:

Total cost of treatment = $TC_{Carrier} + TC_{IP} + TC_{OP} + TC_{SNF} + TC_{HHA}$

One of the first adjustments applied to total cost of treatment is to examine and remove beneficiaries with any negative costs from the data. This process was applied to all five components of cost, in addition to total cost (the sum of the five components, as presented above). The following table shows the total negative costs for each cost component in the study[19]. Note that only components OP (107) and IP (6) actually had negative costs, while the remaining components did not. The table also shows the percent of the total that is negative, which is <=0.1% in each case. Since the percentage is so low, the negative costs were removed from the study sample. A total of 107 beneficiaries are removed, bringing the sample size of beneficiaries from 152,601 to 152,488 beneficiaries (this was presented earlier in the data collection section and is given here in more details).

	Total Negative	Percent
Total	6	0.00393%
Carrier	-	0.00000%
OP	107	0.07012%
IP	6	0.00393%
SNF	-	0.00000%
HHA	-	0.00000%

Table 13: Total occurrences of negative costs by cost component, in 2010

After removing any beneficiaries with negative costs, the next consideration to make is with regards to outlying observations in the data. In health insurance claims, it is not unusual to have some extreme individuals with unusually high costs [63]. These extreme

[19] The results shown in table 9 are for both non-dual and dual beneficiaries

cases are generally better to be left out of the study rather than to keep them in and bias the outcome. One common approach to handle these outlying observations is with the Winsor technique, or winsorization [64]. Winsorization is a technique that censors extreme cases based on a designated percentile level. This technique can be applied to both low as well as high extreme value by designating a range of percentiles (i.e., 1 to 99 percentile). However, in this study, there is no need to censor low cost values, as the minimum cost (after removing negative costs) is at zero. It would not be appropriate to censor those zero cost values to some specified percentile level (for instance, 1 percentile), since it would be desired to study beneficiaries who have zero costs. However, winsorization is applied to the high cost values. In this study, a percentile level of 99 is designated as the value to censor extreme high cost values. Thus any value greater than 99 percentile is set at the 99 percentile. Winsorization is applied to each cost component in addition to total cost.

After removing negative costs and applying the winsorization technique, the following tables give the summary of the cost results, by each cost component and total cost. The first table (table 14) shows the summary for non-dual beneficiaries while the second table (table 15) shows the summary for dual beneficiaries, both for 2010. In both tables, summary measures include the sum, mean, median, min and max[20].

[20] Note that the sum of the cost components does not equal total cost, which is due to winsorization being applied to each of the cost components in addition to total cost.

	N	Sum	Mean	Median	Min	Max
Total	126,942	$853,182,072.00	$6,721.04	$2,220.98	$0.00	$69,410.09
Carrier	126,590	$305,728,412.00	$2,415.11	$1,491.73	$0.00	$17,009.21
OP	95,962	$139,172,365.00	$1,450.29	$545.98	$0.00	$17,266.62
IP	21,892	$299,001,403.00	$13,658.02	$9,076.75	$0.00	$80,658.69
SNF	4,491	$59,294,697.26	$13,203.01	$10,196.46	$0.00	$52,313.05
HHA	9,872	$54,911,844.43	$5,562.38	$3,569.01	$0.00	$32,178.97

Table 14: Summary measures for total cost, for non-dual beneficiaries in 2010

	N	Sum	Mean	Median	Min	Max
Total	25,546	$248,423,519.00	$9,724.56	$3,138.52	$0.00	$92,939.74
Carrier	25,393	$65,978,398.28	$2,598.29	$1,610.23	$0.00	$16,888.99
OP	20,132	$36,362,234.62	$1,806.19	$752.74	$0.00	$20,319.32
IP	5,797	$84,237,071.57	$14,531.15	$8,945.29	$0.00	$94,881.76
SNF	2,024	$30,830,609.56	$15,232.51	$11,948.36	$0.00	$58,194.43
HHA	4,060	$31,291,360.01	$7,707.23	$4,976.32	$0.00	$54,030.22

Table 15: Summary measures for total cost, for dual beneficiaries in 2010

After obtaining the winsorized total costs (including each cost component), a final transformation was to create discrete buckets for the winsorized total cost variable. This new variable is a discrete variable, in contrast to the original total cost variable. Total cost was divided into five equal groups (or quintiles) and the new variable is called cost_all. Cost_all consists of five distinct levels, each containing 25,388 values (or 20 percent of the entire set). Cost levels for cost_all variable are assigned in descending order (i.e., the highest cost level is assigned a value of ‘0’ and the lowest cost level a value of ‘4’).

3.4.1.4.2 Physician Factors

Physician factors consist of analytical factors related to the physician (MD). There are two components that will be considered related to the MD factors, each according to the hypotheses presented earlier. The first part will consider whether primary vs. specialty type physician has an impact on the development of complications in Diabetes patients. In the second part, the impact of urban vs. rural type physician will be evaluated on the development of complications in Diabetes patients. The following will provide a discussion for each of those components in more detail.

One unique aspect of the MD factors (both primary vs. specialty and urban vs. rural) is that they are both applicable only to patients who have had a physician visit during the year. Thus, the data source for this part will be limited to beneficiaries who have had claims for a physician visit in 2010. This is in contrast to all the other variables in the model that use all of the data available for beneficiaries without any such restriction[21]. Thus, all models using the MD factors (both primary vs. specialty and urban vs. rural) will be limited to only beneficiaries who have record of carrier claim utilization. However, in this study it appears that the majority of patients do actually have a physician visit during the year (and hence have utilization in the carrier claim file). In this study, out of 152,488 total beneficiaries (as was given earlier), only 505 do not have any carrier claim utilization. As was shown in tables 10 and 11 above, non-dual beneficiaries have a total of 126,590 beneficiaries (out of 126,942) and dual beneficiaries have a total of 25,393 beneficiaries (out of 25,546) with utilization in the carrier claim file in 2010.

[21] Even though LOS and cost components are also restricted in their data sources, these variables are updated to include zero for non-utilizers. With MD factors, this is not possible and non-utilizers must be eliminated from the study data set.

3.4.1.4.2.1 Primary vs Specialty

To determine whether a primary vs. specialty type physician has an impact on a patient's development of Diabetes complications, it is first necessary to determine the type of physician attributed to a given patient (whether primary or specialty). This is not a straightforward problem, due to the fact that a patient typically has multiple physician visits during the course of the year with a range of specialty types. There is considerable literature on the problem of provider attribution to patients [65, 66]. The approach taken in this dissertation follows closely the process outlined in a related CMS project, the Generating Medicare Physician Quality Performance Results (GEM) Project[22,23]. There are two components to this process: first classifying physicians as primary or specialty and second, attributing a patient to a given physician specialty. The following describes these two components.

First, all of a patient's visits during the base year (2010) are obtained from the carrier claim utilization file. The classification of the physician specialty for each of these visits is also obtained from the carrier claim utilization file. The carrier claim utilization file contains a specialty code associated with the performing physician for each visit on record. These physician specialty codes obtained from the carrier claim utilization file are then linked to a crosswalk available from CMS, the CMS Specialty Codes/Healthcare

[22] http://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/GEM/downloads/GEMMethodologies.pdf
[23] The GEM project created quality measures for physician group practices in 2006-2007 based on Healthcare Effectiveness Data and Information Set (HEDIS) quality measures

Provider Taxonomy Crosswalk[24]. This crosswalk provides a specialty description associated with each of the physician specialty codes.

Not all physician specialties are suitable for consideration, as many represent entities different from a physician provider (this includes physicians, physician assistants and nurse practitioners). For instance, many specialties represent labs, pharmacy or other non-physician type of entities. These specialties are excluded from consideration, as the main objective here is to classify a patient according to that patient's record of visits to a physician provider. Following the approach in the GEM project, a set of qualifying physicians is obtained that restricts the total visits considered in this study. The list of eligible physician providers that are considered in this analysis can be obtained from the GEM project, in Appendix B.

One impact of limiting the physician specialties in this manner is that the data will also be restricted (beyond simply the restriction of beneficiaries having a physician visit in 2010). The impact will be illustrated below (in table 17) where the frequency of a physician specialty by beneficiary is presented.

After obtaining and limiting physician specialties for patient visits from the 2010 carrier claim utilization file, these specialties are classified as either primary or specialty. Table 16 below shows the physician specialties that are grouped as primary. All remaining specialties are subsequently grouped as specialty. One important consideration in the

[24] Available from CMS at http://www.cms.gov/Medicare/Provider-Enrollment-and-Certification/MedicareProviderSupEnroll/downloads/taxonomy.pdf

specialty grouping below is with regards to physician assistants and nurse practitioners. In many cases, these health providers' work varies as primary or specialty, depending on the physician specialty type they are associated with [67]. In the GEM project, these specialties are classified based on the physician practice they are associated with (the practice where the majority of the services by the physician are performed). However grouping physicians by practice is not part of this dissertation[25]. Instead, physician assistant and nurse practitioners are simply considered as primary specialties here.

Primary Specialty
General practice
Family practice
Internal medicine
Geriatric medicine
Preventive medicine
Nurse practitioner
Physician assistant

Table 16: Physician primary specialty types

After each physician visit is classified as either primary or specialty, the next step is to attribute each patients to a physician. Instead of attributing a patient to a specific physician; however, the approach taken here is to attribute a patient to a physician specialty (primary or specialty). Total visits for each patient are obtained in 2010 by primary and by specialty physician types. These totals for primary and specialty physician types are then compared and the maximum is attributed as the physician

[25]

specialty type for that patient[26]. Thus, a patient's physician will be determined according to the specialty type (primary or specialty) most frequently visited for that patient. The following table shows the frequency results for physician specialty type for beneficiaries in the study, captured by a variable called 'Prmry' ('1' means primary and '0' means specialty). These results are shown for non-dual and dual beneficiaries in the year 2010.

	Non-Duals		Duals	
Prmry	**Count**	**Percent**	**Count**	**Percent**
0	69,328	55.00%	12,025	47.82%
1	56,726	45.00%	13,121	52.18%

Table 17: Frequency distribution of Prmry variable, for non-dual and dual beneficiaries

The results in table 17 show that the total data set is reduced from only beneficiaries who have a physician visit in 2010. As was mentioned previously, limiting the physician specialties to only physician providers would further restrict the data set. For non-dual beneficiaries, the total is reduced from 126,590 to 126,054 beneficiaries and for dual beneficiaries the total is reduced from 25,393 to 25,146 beneficiaries.

Finally, one last restriction was considered in attributing patients to physician specialty types. In the Prmry variable above, all physician visits are compared for their specialties being either primary or specialty. However, in the GEM project, only a select set of primary care visits are considered for this comparison. The visits are limited to only those that are office visits or consultations. Thus, provider specialty attribution is limited to only primary care services provided by physicians. This approach is also followed in this dissertation. However, the

[26] In the case of a tie, a primary care visit is assigned as the maximum for that patient

definitions of office visits and consultations are obtained based on Current Procedure Terminology (CPT) codes criteria as defined by the Health Care Cost Institute (HCCI)[27].

A new variable (called 'Prmry_p') is obtained where physician visits are restricted to office visits and consultations. Table 18 shows the frequency results for the variable Prmry_p, for non-dual and dual beneficiaries in 2010. Notice how the percentages change in table 18 in comparison to table 17 (there is an increase in percentage of primary physician type). The analysis portion will be based on Prmry_p variable, as it is the one most likely to capture the specialty type for a given patient.

	Non-Duals		Duals	
Prmry_p	**Count**	**Percent**	**Count**	**Percent**
0	43,872	34.80%	7,249	28.83%
1	82,182	65.20%	17,897	71.17%

Table 18: Frequency distribution of Prmry_p variable, for non-dual and dual beneficiaries

3.4.1.4.2.2 Urban vs Rural

In addition to considering physician specialty type for beneficiaries, a second objective with regards to physician factors is to consider the impact that urban vs. rural physician type has on development of Diabetes complications in patients. As was done above with physician specialty type, it is first important to assign each patient to either a rural or urban physician type. However, as before, this is not a straightforward problem due to patients having multiple physician visit types during the year.

[27] See Appendix 4.4 in the HCCI methodology document available at: http://www.healthcostinstitute.org/files/HCCI%202013%20Methodology%20v3.3.pdf

However, unlike with physician specialty, there is no code to identify urban vs. rural physicians for a beneficiary in the carrier claim utilization file. As a result, each patient's urban vs. rural physician designation will be approximated using the patient's location (instead of the physician's). This should yield a fairly close approximation as it's pretty reasonable to assume that a patient is likely to visit a physician close to where that patient resides in most cases. Information about a beneficiary's location is available in the beneficiary file.

To determine the patient's urban vs. rural location type, there are two steps involved. First, the state and county for a beneficiary are identified using the beneficiary file. Then the state and county are linked to a CMS crosswalk table 'County to CBSA Crosswalk'[28] to obtain the beneficiary's urban vs. rural classification. A patient's physician is then assigned an urban vs. rural classification based on the results of the classification obtained for the beneficiary. Hence, each beneficiary is assigned an urban vs. rural physician type based on that beneficiary's urban vs. rural location.

Based on this approach, a new variable called 'Urb' was created to capture whether a patient is assigned an urban vs. rural physician type. The table below shows the frequency results for the 'Urb' variable, for non-dual and dual beneficiaries in 2010.

[28] For this study, the FY 2012 'County to CBSA Crosswalk' file was obtained from CMS website (http://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/FY-2012-IPPS-Final-Rule-Home-Page-Items/CMS1250507.html)

	Non-Duals		Duals	
Urb	Count	Percent	Count	Percent
Rural	31,525	24.95%	6,514	25.68%
Urban	94,835	75.05%	18,852	74.32%

Table 19: Frequency distribution of Urb variable, for non-dual and dual beneficiaries

As was mentioned above, the distribution displayed in the table above applies only for beneficiaries actually having a visit to a physician during the year (i.e., having a record in the carrier claim utilization file). But another restriction occurs with rural vs. urban, which further reduces the total number of cases available (from a total of 177,945 as shown above). When linking the beneficiary file to the 'County to CBSA Crosswalk' table, there were a total of 326 beneficiaries whose state/county combination did not result with a match. Thus, those 326 cases were not found in the 'County to CBSA Crosswalk' and they were not classified as either rural or urban. These 326 cases would be left out of this part of the analysis. The model for urban vs. rural physician factors will thus only consist of 177,619 cases.

3.4.1.4.3 Patient Cost Sharing

3.4.1.4.3.1 Non-Dual Beneficiaries

For non-dual Medicare beneficiaries, patient cost sharing (or patient total cost) refers to the total amount of cost paid by the patient during the base year. Patient total cost is similar to total cost of treatment discussed above. However, a major distinction is that patient total cost refers to the total amount paid by the patient, instead of by Medicare as

was the case for total cost of treatment previously. Medicare does not cover all expenses, and patients typically have to pay additional out of pocket expenses to cover their care. These patient out of pocket expenses typically include a combination of a deductible, coinsurance and/or copayment.

As was done with total cost of treatment above, patient total cost is obtained by first calculating each component of cost based on each of the claim utilization sources (Carrier, IP, OP, SNF and HHA). Then, as was also done previously, the patient total cost is obtained by summing each of those components of patient costs. The following shows those steps, first the calculation of each cost component, then the sum to obtain the final patient total cost.

i. Carrier

$PTC_{Carrier}$[29] =

Sum (Line Coinsurance Amount[30] + Carrier Claim Cash Deductible Applied Amount)

ii. IP

PTC_{IP} =

Sum (Beneficiary Inpatient Deductible Amount + Beneficiary Part A Coinsurance Liability Amount + Beneficiary Blood Deductible Liability Amount)

[29] PTC stands for Patient Total Cost
[30] Payment obtained at the line Item from carrier claim utilization

iii. OP

PTC_{OP} =

Sum (Beneficiary Part B Deductible Amount + Beneficiary Part B Coinsurance Liability Amount + Beneficiary Blood Deductible Liability Amount)

iv. SNF (same as IP)

PTC_{SNF} =

Sum (Beneficiary Inpatient Deductible Amount + Beneficiary Part A Coinsurance Liability Amount + Beneficiary Blood Deductible Liability Amount)

v. HHA-Populated less than .05%, and is not calculated (set to zero for all home health beneficiaries)[31].

PTC_{HH} = 0

Patient total cost is then calculated as the sum of each of the above components, and is shown in the following formula (in a similar way as total cost of treatment was obtained above):

Patient total cost = $PTC_{Carrier} + PTC_{IP} + PTC_{OP} + PTC_{SNF} + PTC_{HH}$

After calculating patient total cost, additional adjustments are made similar to what was done above with total cost of treatment. First, any beneficiaries with negative patient cost components or patient total cost are identified in the data set so that they can be removed

[31] From http://www.resdac.org/

from the data (as was done with total cost of treatment). However, in this case there were no negative cost values for any of the patient cost components or patient total cost for any of the beneficiaries. Thus, no adjustment was necessary in this case.

In addition to the consideration of negative costs among beneficiaries, outlying patient cost values are censored with the winsorization technique as was done with total cost of treatment. The specifications for censoring applied for patient costs are the same as those used with total costs of treatment-censor only high outlying values at 99 percentile, while leaving the low outlying values uncensored (these values are all zero, due to no negative patient costs among beneficiaries). After applying winsorization to patient costs, the following table shows the summary results for patient costs by components and for total patient cost, for non-dual beneficiaries in year 2010[32].

	N	Sum	Mean	Median	Min	Max
Total	126,942	$164,118,690.00	$1,292.86	$642.99	$0.00	$9,944.13
Carrier	126,590	$85,470,663.13	$675.18	$451.52	$0.00	$4,281.33
OP	95,962	$39,946,990.28	$416.28	$172.60	$0.00	$3,934.21
IP	21,892	$27,236,845.88	$1,244.15	$1,100.00	$0.00	$3,300.00
SNF	4,491	$9,969,184.00	$2,219.81	$275.00	$0.00	$11,000.00
HHA	9,872	$0.00	$0.00	$0.00	$0.00	$0.00

Table 20: Summary measures for patient cost, for non-dual beneficiaries

Similar to what was done with total cost above, a discretized variable for patient total cost was also created. The new variable is called cost_all_p, and contains five discrete buckets of patient total cost, as was done with total cost. Each cost bucket for cost_all_p

[32] Only a summary for non-dual beneficiaries is given here-for dual beneficiaries the results will use Medicaid State investment (covered in the next section).

contains 5,109 cases (or 20% of the whole). The levels for cost_all_p are also assigned in descending order, as was done with cost_all previously.

3.4.1.4.3.2 Dual Beneficiaries

Patient total costs for dual eligible patients are obtained differently than for non-dual Medicare beneficiaries. Dual eligible beneficiaries are generally not responsible for cost sharing requirement as are non-dual beneficiaries. Due to their dual enrollment eligibility (in both Medicare and Medicaid), the out of pocket expenses (or premiums) for dual eligible beneficiaries are paid for by Medicaid [68]. These expenses that Medicaid pays are funded in part by the state (along with a match by the federal government)[33].

To obtain a sense of the patient investment for dual eligible beneficiaries in this dissertation, data regarding each state's Medicaid per beneficiary investment was obtained. This data is available from the CMS Medicaid Statistical Information System (MSIS) State Summary Datamart. The datamart used is for the year 2010, corresponding with the base year of this study. Two components from the 2010 datamart are used to obtain total Medicaid investment per beneficiary by state. First, total Medicaid paid amount is obtained, which shows the total invested by a state in Medicaid. In addition, the unique beneficiary count is also obtained. This count will be used to derive total Medicaid investment by beneficiary in each state. Appendix C shows those results for each state, including total Medicaid paid amount, unique beneficiary count and Medicaid

[33] More detail on the Federal Medical Assistance Percentage (FMAP) is available at http://kff.org/medicaid/state-indicator/federal-matching-rate-and-multiplier/

invested by beneficiary. This latter value will be used in the analysis to evaluate the Medicaid investment per beneficiary corresponding with each dual eligible beneficiary in the study. It is of interest in this dissertation to evaluate the impact that the amount invested in Medicaid per beneficiary has on development of complications Diabetes for dual eligible patients.

After obtaining total Medicaid investment per beneficiary by state, those values are assigned to each beneficiary based on that beneficiary's designated state (this value is obtained from the beneficiary file). There is no need to apply winsorization in this case as was done above, as the values obtained for each individual beneficiary are an average for that beneficiary's state of residence. Thus, extreme values are already smoothed out in this data, eliminating the need for winsorization. The summary results for Medicaid investment by beneficiary in year 2010 is given in table 21 below. The results given below are for all beneficiaries, including all states. For a summary listing by state, Appendix C provides the amount invested in Medicaid by beneficiary by state.

	N	Sum	Mean	Median	Min	Max
Total	25,517	$131,286,625.00	$5,145.07	$4,744.25	$2,870.79	$9,520.27

Table 21: State Medicaid Investment by unique beneficiary, in year 2010

Note that there are some missing beneficiaries in the results above (29 out of a total 25,546 dual eligible beneficiaries, given earlier). The reason is that these beneficiaries are from state and county regions that were not found on the county list (the 'County to CBSA Crosswalk' table, which was discussed above for provider factors). There were 2

cases out of those 29 that actually did have a state and county in the 'County to CBSA Crosswalk' table. However, for those 2 cases, they were both from Puerto Rico-which is not included in the list of Medicaid investment per beneficiary (see Appendix C for a complete list by State). As a result, the data set for patient total cost for dual eligible beneficiaries will only consist of a total of 25,417 total cases (instead of the full 25,546 cases for dual beneficiaries).

Finally, a discretized variable was created for the amount spent by beneficiary in each state (as was done for both total cost and patient total cost above). The new variable is called mcaid_all and also consists of five equal buckets. Each bucket of mcaid_all consists of values. Again, as was done previously, the levels of mcaid_all were assigned in descending order.

3.4.2 Outcome Variables

There will be three outcomes in this study, all relating to Diabetes complications: retinopathy, nephropathy and neuropathy. These are the three main long-term microvascular complications that patients with Diabetes typically develop [7]. This study will seek to evaluate the impact that factors presented up to this point have on development of those complications in Diabetes patients. In particular, the first part of the study will focus on the impact that health risk factors (socio-demographic and health comorbidities) have on development of those three complications. The latter part of the study will focus on answering the three hypotheses presented above, related to the impact

of the analytical factors on development of Diabetes complications in patients: total cost of treatment, MD effect (primary vs. specialty and urban vs. rural) and patient cost sharing (or Medicaid State investment by beneficiary for dual eligible beneficiaries).

Beneficiaries in this study are selected as those diagnosed with Diabetes but having no indication of any long-term Diabetes complications in the first year (2010). In the follow-up year (2011), development of three Diabetes complications is evaluated for each of those beneficiaries. The following describes the process used to identify beneficiaries that develop complications in 2011. The data used for this process involves all five claim utilization source files for 2011 (Carrier, IP, OP, SNF and HHA).

As was performed for 2010, in each of the claim utilization file sources, the primary diagnosis and five additional diagnosis codes were scanned for any occurrence of any of the three Diabetes complications. A diabetes complication is defined based on a set of criteria for each of those three complications (as defined in Appendix A). In this case; however, only these three complications are evaluated for occurrence for a beneficiary in 2011. The additional ICD-9 code range 250.7x-250.9x, which were presented earlier for 2010, will not be considered as an outcome in 2011 (they are only used to remove beneficiaries with a history of any long-term Diabetes complications). As was done in 2010, beneficiaries are defined to have a Diabetes complication with at least one occurrence in claim utilization source files IP, SNF and HHA, or at least two occurrence for claim utilization sources Carrier and OP.

Based on this process, the following table presents the results of the frequency for the Diabetes complications in this study-retinopathy, nephropathy and neuropathy. The results are shown for both non-dual and dual beneficiaries in year 2011.

		Non-Duals		Duals	
Complication		**Count**	**Percent**	**Count**	**Percent**
Retinopathy	no	123,615	97.38%	24,677	96.60%
	yes	3,327	2.62%	869	3.40%
Nephropathy	no	119,330	94.00%	23,704	92.79%
	yes	7,612	6.00%	1,842	7.21%
Neuropathy	no	120,458	94.89%	23,698	92.77%
	yes	6,484	5.11%	1,848	7.23%

Table 22: Frequency distribution of Diabetes complication (retinopathy, nephropathy and neuropathy), for non-dual and dual beneficiaries

Chapter 4 Model

There will be two different types of models that are explored in this dissertation. First, predictive models of Diabetes complications are considered. These predictive models explore the impact that various risk factors have on the development of Diabetes complications in Medicare and dual eligible beneficiaries. The risk factors included in the predictive models include all independent variables presented in Chapter 3 previously, with the exception of not including any of the analytical factors. Thus, the risk factors that have an impact on development of Diabetes complications for beneficiaries are explored in these predictive models.

In addition to the predictive models, explanatory models are then considered. The purpose of explanatory models is to consider the impact of the analytical factors on the development of Diabetes complications in beneficiaries. However, in addition to the analytical factors, these explanatory models will include all the independent variables considered in the predictive models (i.e., all independent variables presented in Chapter 3 are included in the explanatory models). By including the other independent variables in the model allows risk adjustment of the impact that analytical factors have on the development of Diabetes complication rates in beneficiaries. Thus, explanatory models are concerned with evaluation of the risk adjusted impact that analytical factors have on Diabetes complication development in beneficiaries. It is hoped that the findings from those models would lead to conclusion regarding the best approaches of care for beneficiaries.

In both the predictive models and the explanatory models, logistic regression will be used as the modeling approach. The main reason for this modeling approach is due to having a binary outcome in the study. In both models, the outcome is whether a beneficiary develops a certain Diabetes complication in year 2 (i.e., retinopathy in year 2). The covariates in the logistic regression model will include both discrete and continuous variables. All the modeling in this dissertation will be performed using SAS statistical software, version 9.3 (SAS Institute Inc., Cary, NC).

4.1 Predictive Model

The first part of the dissertation will explore predictive models of Diabetes complication rates. These predictive models will include all the independent variables, as presented previously, with the exception of the analytical factors. The following illustrates the mathematical notation of the predictive models.

In equation form, these components can be represented as:

$$\textbf{Logit } (P(Y_i=1)) = \sum_i X_i \alpha_i + \sum_j \text{Comorb}_j \beta_j + \sum_k \text{Util}_k \gamma_k$$

Where,

1. **Logit $(P(Y_i=1) = \ln (P(Y_i=1) / (1 - P(Y_i=1)))$**
2. **Y_i is Diabetes complication outcome (0=no, 1=yes), where**
   i=1, retinopathy; i=2, nephropathy; i=3 neuropathy

3. **X_i are socio-demographic factors (age, sex and race)**
4. **$Comorb_j$ are comorbidity factors**
5. **$Util_k$ are health utilization factors (LOS, SNF stay, outpatient and inpatient admissions and total office visits)**

Each complication (i.e., retinopathy, nephropathy and neuropathy) will be modeled separately. Thus, there will be three predictive models for each complication. This process is repeated for both non-dual and dual beneficiaries. The total models that will be fit will thus be six.

Stepwise logistic regression will be used to model each of the six predictive models. Stepwise regression is a variable selection process where variables are considered in a model based on significance criteria. However, as each variable is added to the model, variables that become non-significant are removed from the model. This process continues until a model with only significant variables remain (based on the set criteria). Stepwise logistic regression will thus allow the predictive models to contain only the significant risk factors (all other non-significant factors are not included in the final results). The criteria used in the stepwise regression process in this study is as follows (based on SAS terminology): slentry=.25 and slstay=.05. In the case of slentry, this refers to the significance probability required for a variable to enter a model for consideration. A fairly relaxed criteria (.25) is used to allow for consideration of as large a number of variables. On the other hand, slstay refers to the significance probability

needed for a variable to remain in the model. A more stringent criteria is used (.05) to ensure that only significant risk factors are included in the final predictive model.

4.2 Explanatory Model

As discussed above, explanatory models will add the analytical factors to the variables already included in the predictive models. However, the purpose of the two types of models is quite different. In the predictive models, the risk factors are evaluated for their significance in development of Diabetes complications in beneficiaries. However, explanatory models will use the risk factors to allow for risk adjustment of the impact that analytical factors have on development of Diabetes complication development in beneficiaries.

The modeling approach for explanatory models will not use stepwise selection, as was the case with the predictive models. The reason is that there is no need to only consider significant risk factors in risk adjustment. All risk factors are left in the model, along with the analytical factors. The modeling approach will simply use logistic regression to evaluate the impact that the risk adjusted analytical factors have on the development of Diabetes complications in beneficiaries. However, only the impact of the analytical factors will be of interest in this case, as the remaining risk factors are used solely for risk adjustment of the analytical factors. The results will simply include the risk adjusted impact of the analytical factors on the development of Diabetes complications in beneficiaries.

The following will illustrate the mathematical notation of the explanatory models. Note that for each hypothesis (i.e., corresponding to each analytical factor), there will be six different explanatory models-three based on each outcome, and this is repeated for both non-dual and dual beneficiaries (as was the case with the predictive models). Hence, there will be a total of 18 total explanatory models, after consider the three different hypotheses.

4.2.1 Hypothesis I

The variables in the explanatory models for hypothesis I include all the variables presented above in the predictive model. In addition, treatment cost levels are also added to the list of covariates. The following shows the notation for the treatment cost levels.

$$\sum_k \mathbf{Treat}_k \, \beta_k$$

Where $\mathbf{Treat}_k$ refers to the cost levels for total treatment cost. There are a total of 5 cost levels, ranging from the lowest cost (level '4') to the highest cost (level '0').

4.2.2 Hypothesis II

The variables in the explanatory models for hypothesis II include all the variables in the predictive model. In addition, two physician factors are added to the model: specialist vs.

generalist and urban vs. rural factors. Also, the interaction between those two physician factors is also added. The notation for the physician factors in the model is as follows:

$$\sum_x \mathbf{Phys1_x}\,\alpha 1_x + \sum_y \mathbf{Phys2_y}\,\alpha 2_y + \sum_x \sum_y \mathbf{Phys1_x}\,\mathbf{Phys2_y}\,\alpha 3_{xy}$$

Where $\mathbf{Phys1_x}\,\mathbf{Phys2_y}$ refer to the specialist vs. generalist and urban vs. rural physician factors, respectively (along with their interaction). Both of the physician factors consist of two levels.

4.2.3 Hypothesis III

4.2.3.1 Non-Dual Beneficiaries

The variables in the explanatory models for hypothesis II include all the variables in the predictive model. In addition, total patient cost sharing levels are also added to the list of covariates. The following shows the notation for the total patient cost sharing levels.

$$\sum_n \mathbf{Patient_n}\,\delta_n$$

Where $\mathbf{Patient_n}$ refers to the levels for total patient cost sharing. There are a total of 5 levels, ranging from the lowest cost (level ‘4’) to the highest cost (level ‘0’)

4.2.3.1 Dual Beneficiaries

For dual beneficiaries, instead of adding total patient cost sharing, state per beneficiary investment is added to the variables in the predictive model. This is due to dual beneficiaries receiving cost sharing payment from the Medicaid program, as was discussed. The following shows the notation for the state per beneficiary investment in Medicaid:

$$\sum_{m} \mathbf{Capita}_{m}\, \rho_{m}$$

Where $\mathbf{Capita}_{m}$ refers to the cost levels for state per beneficiary investment. There are a total of 5 levels, ranging from the lowest cost (level '4') to the highest cost (level '0')

Chapter 5 Results and Discussion

5.1 Predictive Model Results

For the predictive models, results shown will include the outcomes of the stepwise logistic regression models. The outcomes will show the significant factors for each model. Those are the factors that are considered predictive of the Diabetes complication in each model. In the tables shown, only the odds ratios are presented for each significant factor, along with confidence limits for those odds ratios. In addition, in Appendix E, the full results from the model output, including parameter estimates and significance levels are shown. Finally, a graphical output of the odds ratios are also included in Appendix E. Those graphs plot the odds ratio in descending order, to highlight those factor determined to be the most predictive of the Diabetes complication for each model.

In each of the predictive models, only positive significant comorbidity risk factors were allowed to remain in the model. Thus, if a beneficiary had a negative significant comorbidity (i.e., having the condition improved the complication outcome rate), then that comorbidity factor was removed from the model, and the model was re-fit. The justification for this process is that there is acceptable clinical interpretation for this result and it is removed from consideration in the model[34].

5.1.1 Non-Dual Beneficiaries

[34] For all model results presented below, the variables are shown in abbreviated format. For a more detailed description of the variables, refer to Appendix D, which contains a glossary of the model variables.

5.1.1.1 Retinopathy

The following table shows the odds ratios for the significant factors for the predictive model of retinopathy complication among non-dual beneficiaries. For this model, two comorbidity factors were removed from consideration (due to having negative significant results): copd and rheum_a. The factors were removed and the model was re-fit in each case. The final results are shown in Table 23.

	Odds Ratio	Lower 95% CL	Upper 95% CL
race_1 Other vs White	1.111	0.937	1.317
race_1 Black vs White	1.522	1.366	1.696
ov_1	1.008	1.004	1.013
snf_stay 1 vs 0	0.792	0.645	0.973
HPTN_C 1 vs 0	1.131	1.01	1.267
Lymp 1 vs 0	1.347	1.02	1.78

Table 23: Odds ratios (with 95% CLs) for retinopathy complication, for non-dual beneficiaries

5.1.1.2 Nephropathy

The following table shows the results for the nephropathy complication, among non-dual beneficiaries. For this model, there were no negative significant factors, and none were removed from the model for re-fitting. However, one variable was removed initially from consideration, the rf variable (or renal failure). The rf variable is very highly correlated with nephropathy and it was of interest to evaluate the other predictive factors that had an impact on development of nephropathy complication.

		Odds Ratio	Lower 95% CL	Upper 95% CL
sex	**M vs F**	1.319	1.258	1.384
race_1	**Other vs White**	1.052	0.933	1.187
race_1	**Black vs White**	1.271	1.172	1.379
age_grp	**80_over vs 64_to_69**	1.837	1.719	1.963
age_grp	**75_to_79 vs 64_to_69**	1.458	1.359	1.564
age_grp	**70_to_74 vs 64_to_69**	1.202	1.123	1.287
op_tot_stay_1		1.013	1.009	1.016
ov_1		1.003	1	1.007
snf_stay	**1 vs 0**	0.852	0.759	0.956
CHF	**1 vs 0**	1.63	1.534	1.733
PCD	**1 vs 0**	1.192	1.065	1.335
PVD	**1 vs 0**	1.134	1.069	1.204
HPTN_NC	**1 vs 0**	1.479	1.356	1.614
HPTN_C	**1 vs 0**	1.561	1.458	1.671
COPD	**1 vs 0**	1.097	1.035	1.164
Obesity	**1 vs 0**	1.193	1.096	1.3
Fluid	**1 vs 0**	1.323	1.235	1.418
DA	**1 vs 0**	1.167	1.083	1.257

Table 24: Odds ratios (with 95% CLs) for nephropathy complication, for non-dual beneficiaries

5.1.1.3 Neuropathy

The following table shows the results for the predictive factors for the neuropathy complication predictive model, among non-dual beneficiaries. Three comorbidity were removed and the model re-fit, due to having negative significant results. The factors removed included: coag, tumor and lymp.

		Odds Ratio	Lower 95% CL	Upper 95% CL
sex	**M vs F**	1.076	1.022	1.132
race_1	**Other vs White**	0.815	0.706	0.941
race_1	**Black vs White**	1.181	1.081	1.291
age_grp	**80_over vs 64_to_6**	1.146	1.067	1.23
age_grp	**75_to_7 vs 64_to_6**	1.076	1	1.158
age_grp	**70_to_7 vs 64_to_6**	1.026	0.958	1.098
op_tot_stay_1		1.006	1.002	1.01
ov_1		1.023	1.02	1.026
snf_stay	**1 vs 0**	1.227	1.09	1.38
CHF	**1 vs 0**	1.104	1.029	1.185
PVD	**1 vs 0**	1.359	1.277	1.446
OthND	**1 vs 0**	1.214	1.097	1.344
COPD	**1 vs 0**	1.065	1.001	1.133
RF	**1 vs 0**	1.19	1.067	1.328
Rheum_A	**1 vs 0**	1.119	1.012	1.237
Obesity	**1 vs 0**	1.3	1.192	1.418
Alcohol	**1 vs 0**	1.439	1.097	1.888
Drug	**1 vs 0**	1.664	1.25	2.217
Dep	**1 vs 0**	1.192	1.098	1.295

Table 25: Odds ratios (with 95% CLs) for neuropathy complication, for non-dual beneficiaries

5.1.2 Dual Beneficiaries

5.1.2.1 Retinopathy

The following table shows the odds ratios for the significant factors in the predictive model for retinopathy complication, among dual beneficiaries. The following comorbidity factors were removed and the model re-fit, due to having negative significance: copd and wl.

	Odds Ratio	Lower 95% CL	Upper 95% CL
race_1 Other vs White	1.302	1.108	1.531
race_1 Black vs White	1.234	1.035	1.472
HPTN_NC 1 vs 0	1.351	1.039	1.757
RF 1 vs 0	1.381	1.064	1.792

Table 26: Odds ratios (with 95% CLs) for retinopathy complication, for dual beneficiaries

5.1.2.2 Nephropathy

The following table shows the odds ratios for the significant factors in the predictive model for nephropathy complication, among dual beneficiaries. In addition to removing the rf comorbidity factor (as was done with non-dual beneficiaries), the psycho comorbidity factor was also removed due to having negative significance.

	Odds Ratio	Lower 95% CL	Upper 95% CL
sex M vs F	1.217	1.096	1.353
race_1 Other vs White	0.866	0.764	0.982
race_1 Black vs White	1.083	0.956	1.226
age_grp 80_over vs 64_to_6	1.463	1.284	1.667
age_grp 75_to_7 vs 64_to_6	1.216	1.055	1.401
age_grp 70_to_7 vs 64_to_6	0.964	0.838	1.109
op_tot_stay_1	1.007	1	1.013
snf_stay 1 vs 0	0.804	0.674	0.959
CHF 1 vs 0	1.49	1.333	1.667
PVD 1 vs 0	1.121	1.005	1.25
HPTN_NC 1 vs 0	1.364	1.129	1.647
HPTN_C 1 vs 0	1.575	1.388	1.787
Obesity 1 vs 0	1.241	1.062	1.452
Fluid 1 vs 0	1.429	1.263	1.616

Table 27: Odds ratios (with 95% CLs) for nephropathy complication, for dual beneficiaries

5.1.2.3 Neuropathy

The following table shows the odds ratios results for the significant factors in the predictive model for neuropathy complication. Only the psycho comorbidity factor was removed and the model re-fit, due to being negative significant in the model.

	Odds Ratio	Lower 95% CL	Upper 95% CL
age_grp 80_over vs 64_to_6	0.88	0.769	1.006
age_grp 75_to_7 vs 64_to_6	1.015	0.884	1.165
age_grp 70_to_7 vs 64_to_6	1.069	0.941	1.214
ov_1	1.018	1.012	1.023
CHF 1 vs 0	1.261	1.127	1.411
PVD 1 vs 0	1.338	1.201	1.49
RF 1 vs 0	1.274	1.058	1.534
Rheum_A 1 vs 0	1.213	1.02	1.443
Obesity 1 vs 0	1.331	1.147	1.543
Drug 1 vs 0	1.665	1.147	2.418
Dep 1 vs 0	1.213	1.075	1.37

Table 28: Odds ratios (with 95% CLs) for neuropathy complication, for dual beneficiaries

5.1.3 Individual Risk Profiles

In addition to the odds ratios for the predictive factors in each model for the Diabetes complications, individual risk profiles were also created. Based on the significant risk factors generated in each model, the complication rate for a range of risk profiles based on the risk factors is obtained. The complication rate for the two most extreme risk profiles (best and worst) are presented in the figures below (Figures 2 shows the results

for non-dual beneficiaries and Figure 3 for dual beneficiaries)[35]. It is interesting to note the wider range for the complication rates in the case of nephropathy and neuropathy, compared to retinopathy. This is due to retinopathy complication having resulted in fewer risk factors than the other complications. In general, retinopathy has been the least predictive among all the complications. Both nephropathy and neuropathy were comparable in their prediction results. Nonetheless, in all three cases, it is interesting to note that a risk profile provides a useful result to evaluate beneficiaries' potential risk of developing a complication in the following year, where no such complication has been so far detected. Care management approaches can be implemented for various risk profiles among beneficiaries to allow for improved outcomes with delay of the complication development. This is the purpose of the explanatory models, and their results will be presented next.

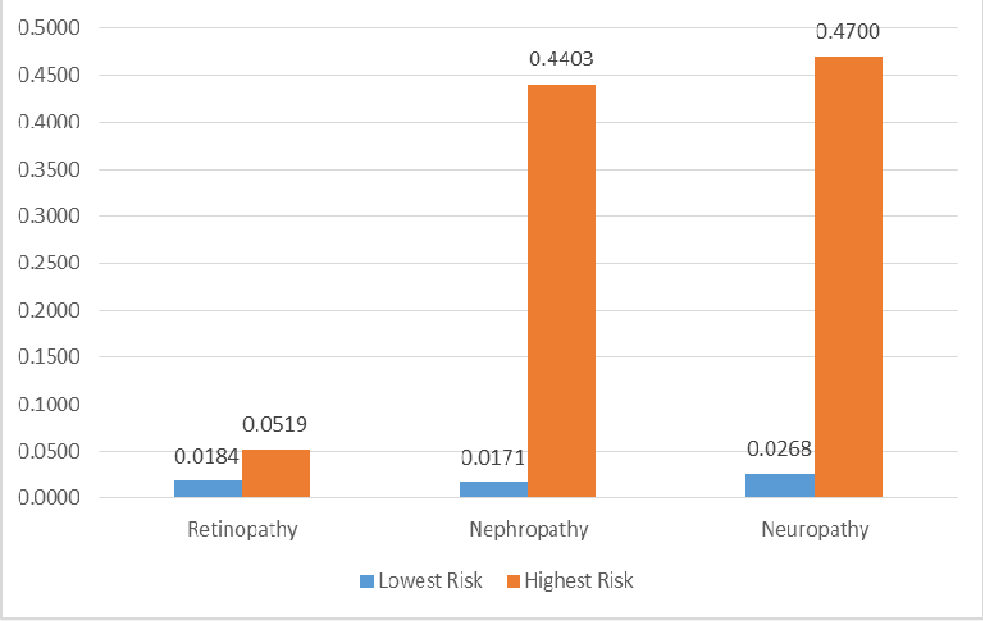

Figure 2: Complication rate by risk profile, for non-dual beneficiaries

[35] For continuous significant factors (i.e., los, total office visits), best and worst were defined as 90th and 10th percentiles, respectively

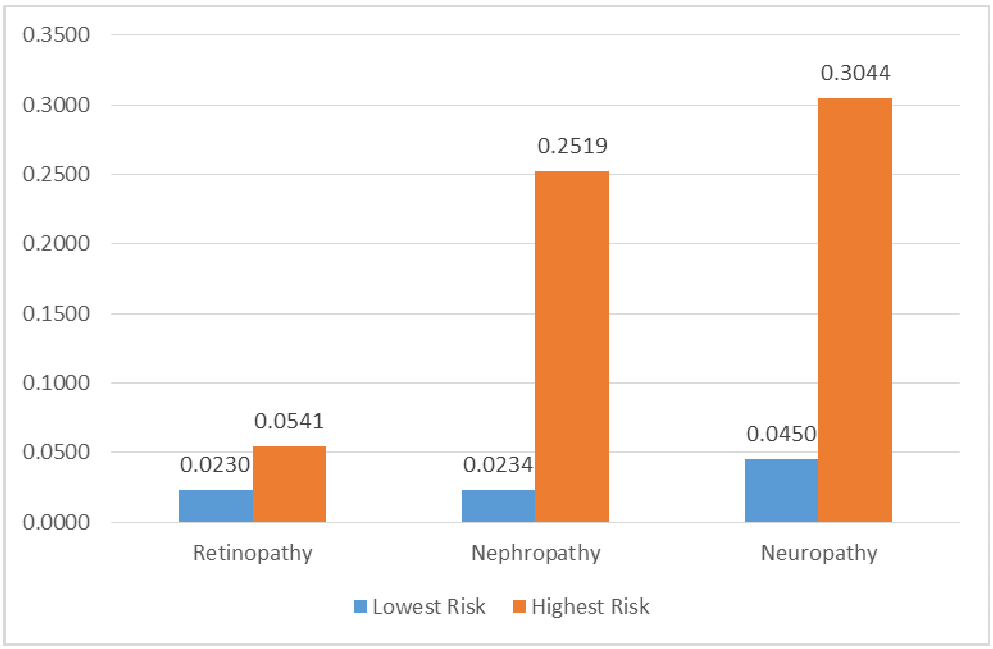

Figure 3: Complication rate by risk profile, for dual beneficiaries

5.2 Explanatory Model Results

The results for the explanatory models will include estimate results for only the analytical factors (corresponding with each of the hypotheses). Appendix F contains a more detailed listing of the estimates for all the variables in the model. These remaining variables are the risk adjustment variables for each of the analytical factors, as was discussed prior. However, the only variable of interest in evaluation of each hypothesis is the effect that the analytical factor has on the complication outcome, risk adjusted for all the other variables that depict the various risk levels of the beneficiaries.

In all the estimate results presented, the estimate of the analytical factor is shown along with the standard error (in parenthesis) as well as the p-value. In all analysis, a p-value of less than 0.05 was considered to be statistically significant. Estimates found statistically significant are accompanied with an asterisks (*) in the results below.

In all the models presented, comorbidity risk factors are based on Elixhauser factors (as was presented). However, two other comorbidity risk adjustment factors are considered, in order to consider the impact that these may have on the results beyond those based on Elixhauser. The first alternative risk adjustment factor used is the Medicare Hierarchical Condition Category (HCC) risk score [69]. This risk score is calculated based on ICD-9 diagnosis variables, socio-demographics factors as well as other related factors (such as enrollment in Medicaid). HCC is derived as a single risk score, which is used in place of the 29 Elixhauser variables in risk adjustment model. The risk score is transformed into a discrete variable by creating five groups (or quintiles)[36].

The other approach used as an alternative to Elixhauser risk adjustment is calculated based on the total number of comorbidities that a beneficiary has. These comorbidities are actually based on the Elixhauser factors, where a beneficiary's total comorbidities are summed up based on their total number of Elixhauser conditions. A tiered variable is created based on the beneficiary having 0-2 conditions (first tier), 3-4 conditions (second tier) and >=5 conditions (third tier). The variable for the total number of comorbidities for a beneficiary is called 'Comorb', and this notation will be used in the tables below.

[36] The risk score used in the models is the community risk score (instead of the institutional risk score or any of the other derived risk scores)

The results below are presented first based on the Elixhauser risk adjustment. These results are presented for each hypothesis, for both non-dual and dual beneficiaries. In addition to the results based on Elixhauser risk adjustment, results based on HCC and Comorb risk adjustments are also presented. However, unlike with Elixhauser risk adjustment, HCC and Comorb risk adjustment results are not presented in every case. HCC and Comorb risk adjustment results are only presented when they demonstrate a difference of some significance from results obtained based on Elixhauser risk adjustment. If the results based on HCC and Comorb risk adjustment are comparable to the results based on Elixhauser risk adjustment, then only Elixhauser risk adjustment are shown. Conclusions for those cases will be derived simply from the results shown based on Elixhauser risk adjustment.

5.2.1 Hypothesis I

5.2.1.1 Non-Dual Beneficiaries

The following table shows the estimate results for the total cost of treatment analytical factor (cost_all). The results are shown for non-dual beneficiaries. In these results, cost_all estimates are shown relative to level '4' in each case (which is the lowest cost level). Based on the results, only retinopathy and neuropathy show statistical significance. For both of these complications, it appears that higher cost of treatment is associated with increase in complication rates. This result is not in agreement with what

was expected (it was believed that an increase in treatment investment would lead to lowered complication rates in beneficiaries). Further exploration was performed for all of the complications using both HCC and Comorb risk adjustment methods, as was previously discussed.

		Retinopathy		Nephropathy		Neuropathy	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
cost_all	0	.317 (.079)*	<.0001	.004 (.054)	0.9355	.534 (.057)*	<.0001
cost_all	1	.307 (.064)*	<.0001	.056 (.045)	0.2176	.459 (.049)*	<.0001
cost_all	2	.291 (.060)*	<.0001	-.001 (.044)	0.9899	.332 (.048)*	<.0001
cost_all	3	.139 (.060)*	0.021	.076 (.042)*	0.072	.164 (.048)*	0.0007
cost_all	4	0	.	0	.	0	.

Table 29: Parameter estimate results for hypothesis I (cost_all), for non-dual beneficiaries

The results in table 30 show total cost of treatment based on both HCC and Comorb risk adjustment. The results yield interesting conclusions, in comparison to the above results. First, for retinopathy, it appears that although the estimates are positively significant, there is a decreasing trend from level '2' to level '0'. This is observed with both HCC and Comorb risk adjustment. This indicates that as treatment investment increases from level '2' and beyond, there is a lower rate of complication for retinopathy. For nephropathy, although the results were not significant in the table above they appear significant in this case. In fact, the estimates show negative significance in all cases (with the exception of level '3'). These negative estimates are decreasing as investment increases, meaning that rate of complication for nephropathy continues to improve relative to level '4' with an increase in treatment investment. Finally for neuropathy, in general the results appear consistent with the previous table with one small exception.

For HCC risk adjustment, there is a slight dip in going from level '1' to level '0'. This means that at very high treatment investments, the higher investment shows improvement in neuropathy complication rate (only based on HCC risk adjustment).

		HCC		Comorb	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
retinopathy					
cost_all	0	.214 (.081)*	0.008	.184 (.080)*	0.022
cost_all	1	.228 (.065)*	0.001	.194 (.065)*	0.003
cost_all	2	.232 (.061)*	0.0001	.209 (061)*	0.0007
cost_all	3	.104 (.061)	0.087	.092 (.061)	0.129
cost_all	4	0	.	0	.
nephropathy					
cost_all	0	-.289 (.053)*	<.0001	-.174 (.053)*	0.001
cost_all	1	-.164 (.045)*	0.0003	-.132 (.045)*	0.004
cost_all	2	-.148 (.044)*	0.0007	-.139 (.044)*	0.001
cost_all	3	-.008 (.042)	0.8498	.0003 (.042)	0.9942
cost_all	4	0	.	0	.
neuropathy					
cost_all	0	.141 (.058)*	0.015	.387 (.058)*	<.0001
cost_all	1	.172 (.049)*	0.001	.337 (.049)*	<.0001
cost_all	2	.118 (.049)*	0.015	.233 (.048)*	<.0001
cost_all	3	.032 (.049)	0.509	.102 (.049)*	0.037
cost_all	4	0	.	0	.

Table 30: Parameter estimate results for hypothesis I (cost_all) for non-dual beneficiaries, using HCC and Comorb risk adjustment

5.2.1.2 Dual Beneficiaries

The following table shows the estimate results for the total cost of treatment analytical factor (cost_all) for dual beneficiaries. In these results, cost_all estimates are shown relative to level '4' in each case (which is the lowest cost level). The results are somewhat comparable to those for non-dual beneficiaries above. Only retinopathy and

neuropathy complications show statistically significant results; nephropathy does not show any statistical significance. In both retinopathy and neuropathy, it appears that there is a positive trend, where higher treatment investment leads to higher complication rate (again, this is not what was hypothesized). However, for retinopathy, there is a dip in going from level '2' to level '1', meaning that increasing investment at those levels does lead to improved outcome. This would have to be corroborated with the other risk adjusters, shown below.

		Retinopathy		Nephropathy		Neuropathy	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
cost_all	0	.632 (.158)*	<.0001	.019 (.115)	0.8621	.962 (.112)*	<.0001
cost_all	1	.354 (.129)*	0.0065	.018 (.094)	0.8475	.739 (.096)*	<.0001
cost_all	2	.429 (.119)*	0.0003	.033 (.089)	0.7073	.579 (.093)*	<.0001
cost_all	3	.154 (.119)	0.1942	.075 (.086)	0.3807	.357 (.095)*	0.0002
cost_all	4	0	.	0	.	0	.

Table 31: Parameter estimate results for hypothesis I (cost_all), for dual beneficiaries

In Table 32, the results for the estimates of total cost of treatment are shown using HCC and Comorb risk adjustment. These results were not as impactful as they were for non-dual beneficiaries. Retinopathy has two significant values (at level '2' and level '0') and both support a positive increasing trend. Likewise, for neuropathy, the results support a positive trend, similar to the results based on Elixhauser risk adjustment. For nephropathy, using HCC risk adjustment shows significant results, at level '1' and level '0'. Both of these results are negatively significant, meaning that they both are improvements from level '4' (the lowest level) and level '0' is a higher improvement than level '1'. These conclusions are more in line with the expected hypothesis result.

However, these are not replicated with Comorb risk adjustment and they do not show statistical significance for other levels (beyond levels '0' and '1'). They appear to have some validity but further investigation may be warranted to make a conclusion regarding nephropathy complication rate.

		HCC		Comorb	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
retinopathy					
cost_all	0	.444 (.161)*	0.006	.485 (.159)*	0.002
cost_all	1	.2 (.132)	0.131	.217 (.133)	0.103
cost_all	2	.324 (.119)*	0.007	.324 (.121)*	0.008
cost_all	3	.097 (.119)	0.418	.089 (.120)	0.459
cost_all	4	0	.	0	.
nephropathy					
cost_all	0	-.280 (.113)*	0.013	-.131 (.111)	0.238
cost_all	1	-.204 (.093)*	0.029	-.154 (.094)	0.1
cost_all	2	-.133 (.089)	0.133	-.144 (.089)	0.109
cost_all	3	-.006 (.085)	0.942	-.036 (.086)	0.673
cost_all	4	0	.	0	.
neuropathy					
cost_all	0	.740 (.115)*	<.0001	.843 (.114)*	<.0001
cost_all	1	.544 (.098)*	<.0001	.600 (.099)*	<.0001
cost_all	2	.439 (.095)*	<.0001	.459 (.096)*	<.0001
cost_all	3	.269 (.095)*	0.005	.273 (.096)*	0.004
cost_all	4	0	.	0	.

Table 32: Parameter estimate results for hypothesis I (cost_all) for dual beneficiaries, using HCC and Comorb risk adjustment

5.2.2 Hypothesis II

5.2.2.1 Non-Dual Beneficiaries

The following table shows the estimate results for the physician analytical factor, both generalist vs. specialist (prmry_p) and urban vs. rural (urb). The results are shown for non-dual beneficiaries. In these results, prmry_p estimates are shown relative to level '1' (primary) and urb estimates are shown relative to 'urban' level. The results based on Elixhauser risk adjustment were comparable to those based on HCC and Comorb risk adjustment, and those results were not shown. However, there was one distinction that appeared with relation to nephropathy complication, which will be discussed further.

Based on the results below, retinopathy and neuropathy both appear to have higher complication rates among specialist vs. primary care physician. For both of these complications, the results are not significant with regards to urban vs. rural physician. For nephropathy complication on the other hand, the reverse is true-primary vs. specialist does not have significant results; however, urban vs. rural providers show statistical significance and it appears that rural to have lower complication rates than urban providers. However, primary vs. specialist did appear significant for nephropathy when using both HCC and Comorb risk adjustment. Based on those risk adjustments, specialist appeared to have a lower complication rate than generalist for nephropathy (which is the trend obtained using Elixhauser but which was not statistically significant). Thus, there is evidence that for nephropathy, complicate rates improve both with visiting a specialist as well as a rural provider.

		Retinopathy		Nephropathy		Neuropathy	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
prmry_p	0	.088 (.044)*	0.0452	-.010 (.030)	0.7315	.119 (.031)*	0.0001
prmry_p	1	0	.	0	.	0	.
urb	rural	-.031 (.053)	0.5613	-.118 (.037)*	0.0013	-.045 (.039)	0.2434
urb	urban	0	.	0	.	0	.

Table 33: Parameter estimate results for hypothesis II (prmry_p and urb), for non-dual beneficiaries

5.2.2.2 Dual Beneficiaries

Table 34 shows the estimate results for the physician analytical factor, both generalist vs. specialist (prmry_p) and urban vs. rural (urb), among dual beneficiaries. The results are similar in format to the results shown in Table 33 above.

For dual beneficiaries, only retinopathy showed any statistical significance for specialist vs. primary care physician, with specialist having higher complication rate than primary care physician (similar to the result obtained for non-dual beneficiaries). For urban vs. rural physician type, only neuropathy shows significant results, and in this case rural appear to have better complication rate results than urban physicians. This is comparable to the previous result obtained for nephropathy for non-dual beneficiaries. Nephropathy does not show any statistically significant results, for neither specialist vs. generalist or urban vs. rural physician type.

		Retinopathy		Nephropathy		Neuropathy	
Parameter		Estimate (SE)	p-value	Estimate (SE)	p-value	Estimate (SE)	p-value
prmry_p	0	.177 (.087)*	0.0415	-.014 (.065)	0.8328	.027 (.062)	0.6665
prmry_p	1	0	.	0	.	0	.
urb	rural	-.161 (.105)	0.1247	.002 (.072)	0.9754	-.173 (.073)*	0.0182
urb	urban	0	.	0	.	0	.

Table 34: Parameter estimate results for hypothesis II (prmry_p and urb), for dual beneficiaries

5.2.3 Hypothesis III

5.2.3.1 Non-Dual Beneficiaries

The following table shows the estimate results for the patient total cost sharing analytical factor (cost_all_p). The results are shown for non-dual beneficiaries. In these results, cost_all_p estimates are shown relative to level '4' in each case (which is the lowest cost level). The results using Elixhauser risk adjustment are pretty straightforward (and comparable to those obtained for total cost of treatment in hypothesis I): both retinopathy and neuropathy show positive significant trend, showing that increase in total patient cost sharing leads to higher complication rates (or put another way, reduced patient cost sharing leads to better outcomes with lower complication rates). Nephropathy does not show any statistical significance using Elixhauser risk adjustment.

		Retinopathy		Nephropathy		Neuropathy	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
cost_all_p	0	.345 (.079)*	<.0001	-.079 (.054)	0.1478	.410 (.057)*	<.0001
cost_all_p	1	.269 (.063)*	<.0001	-.0003 (.044)	0.9952	.400 (.048)*	<.0001
cost_all_p	2	.260 (.060)*	<.0001	-.026 (.043)	0.5517	.265 (.047)*	<.0001
cost_all_p	3	.103 (.059)	0.0869	.025 (.042)	0.554	.154 (.048)*	0.0013
cost_all_p	4	0	.	0	.	0	.

Table 35: Parameter estimate results for hypothesis III (cost_all_p), for non-dual beneficiaries

The results in table 36 are based on using HCC and Comorb risk adjustments. For retinopathy, there is positive statistical significance at levels ‘2’ up to level ‘0’. However, there appears to be a dip going from level ‘2’ to level ‘1’, appearing for both HCC and Comorb risk adjustments. This means that at level ‘2’ and higher, complication rates for retinopathy are higher than at level ‘4’, although there is an improvement in complication rate from going from level ‘2’ to level ‘1’. Nephropathy shows significant results with HCC and Comorb risk adjustment, in contrast to the results based on Elixhauser risk adjustment. There is decreasing trend from going from level ‘2’ and upward, where each increasing level shows improvement in nephropathy complication rate. Finally for neuropathy, HCC risk adjustment shows a positive increasing trend (similar to that obtained based on Elixhauser risk adjustment), with the exception at level ‘0’ where there appears to be a dip-or an improvement in outcome-in comparison to level ‘1’.

		HCC		Comorb	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
retinopathy					
cost_all	0	.252 (.080)*	0.002	.217 (.079)*	0.007
cost_all	1	.201 (.064)*	0.002	.166 (.064)*	0.01
cost_all	2	.207 (.061)*	0.001	.183 (.061)*	0.003
cost_all	3	.079 (.060)	0.188	.061 (.060)	0.312
cost_all	4	0	.	0	.
nephropathy					
cost_all	0	-.349 (.053)*	<.0001	-.272 (.053)*	<.0001
cost_all	1	-.213 (.044)*	<.0001	-.183 (.044)*	<.0001
cost_all	2	-.181 (.043)*	<.0001	-.173 (.043)*	<.0001
cost_all	3	-.057 (.042)	0.169	-.05 (.042)	0.229
cost_all	4	0	.	0	.
neuropathy					
cost_all	0	.062 (.058)	0.283	.270 (.058)*	<.0001
cost_all	1	.132 (.049)*	0.007	.286 (.049)*	<.0001
cost_all	2	.065 (.048)	0.174	.173 (.048)*	0.0003
cost_all	3	.034 (.048)	0.476	.099 (.048)*	0.037
cost_all	4	0	.	0	.

Table 36: Parameter estimate results for hypothesis III (cost_all_p) for non-dual beneficiaries, using HCC and Comorb risk adjustment

5.2.3.2 Dual Beneficiaries

Table 37 shows the estimate results for the state per beneficiary Medicaid investment analytical factor (mcaid_all). The results are for dual beneficiaries. In these results, mcaid_all estimates are shown relative to level '4' in each case (which is the lowest cost per beneficiary level). Based on the results shown, retinopathy appears to have negative significant results for all levels, with the exception of level '0'. This means that higher state Medicaid investment per beneficiary leads to improved outcome in complication rate for retinopathy, up to level '1'. There is not enough evidence to make a conclusion regarding level '0'. For nephropathy, levels '3' and '0' are both negatively significant,

which means that state Medicaid investment per beneficiary at those levels leads to improved outcomes in comparison to state Medicaid investment per beneficiary at level '4' (the lowest level). Finally, neuropathy does not show any significant results and no conclusions can be made regarding its relation to state Medicaid investment per beneficiary levels.

		Retinopathy		Nephropathy		Neuropathy	
Parameter		**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**	**Estimate (SE)**	**p-value**
mcaid_all	0	-.005 (.101)	0.963	-.252 (.081)*	0.0018	-.038 (.079)	0.6331
mcaid_all	1	-.414 (.117)*	0.0004	-.029 (.081)	0.7179	-.091 (.084)	0.2747
mcaid_all	2	-.380 (.110)*	0.0006	-.038 (.078)	0.6267	.150 (.077)	0.0512
mcaid_all	3	-.314 (.113)*	0.0054	-.234 (.085)*	0.0057	.128 (.080)	0.1104
mcaid_all	4	0	.	0	.	0	.

Table 37: Parameter estimate results for hypothesis II (mcaid_all), for dual beneficiaries

5.3 Model Performance

The last part of this analysis will present the measures of performance for the models in the study. The model performance measure considered is the area under the receiver operating curve (ROC), also known as the AUC (for area under the curve) or c-statistic. This measure captures the ability of the model to classify outcomes correctly [70]. The values for the c-statistic range from 0.5 to 1, with increasing levels signifying a better performing model.

Table 38 shows the c-statistic results for both the predictive and explanatory models in the study.

			Explanatory		
Model		**Predictive**	**Hyp I**	**Hyp II**	**Hyp III**
Non-dual	*retinopathy*	0.541	0.563	0.555	0.561
	nephropathy	0.639	0.694	0.694	0.694
	neuropathy	0.604	0.609	0.606	0.607
Dual	*retinopathy*	0.543	0.591	0.585	0.592
	nephropathy	0.619	0.682	0.681	0.684
	neuropathy	0.600	0.622	0.612	0.611

Table 38: C-statistic performance results for predictive and explanatory models in study

The results in Table 38 show relatively moderate model predictive capability. In general, both nephropathy and neuropathy demonstrate better model performances than does retinopathy (this is the case for both non-dual and dual beneficiaries). Nephropathy typically has a slightly better performance than does neuropathy. Also, for both retinopathy and neuropathy, dual beneficiaries appear to have better model performances than non-dual beneficiaries. This is the opposite; however, with nephropathy, where model performance for non-dual beneficiaries is better than for dual beneficiaries. Finally, for all complications, explanatory models have superior performance than predictive models[37]. A demonstration for one of the models (nephropathy for dual beneficiaries for Hypothesis II) is shown in Figure 4 below. The figure illustrates the distribution of the predicted outcomes (y_pred) stratified based on actual outcome (y=0 or 1, if a beneficiary has a nephropathy complication). As expected, the figure shows a

[37] This is expected, as the explanatory models add analytical factors to the predictive models, which would improve performance.

higher frequency of higher predicted outcomes for the case when y=1 (showing an added peak for those higher predicted outcomes)[38]. However, the model's discriminating ability is not very strong (where c-statistic is .681, as was shown in Table 38). A model with higher c-statistic would have a greater discrimination capability than what Figure 4 illustrates, and likely a higher second peak for the case where y=1.

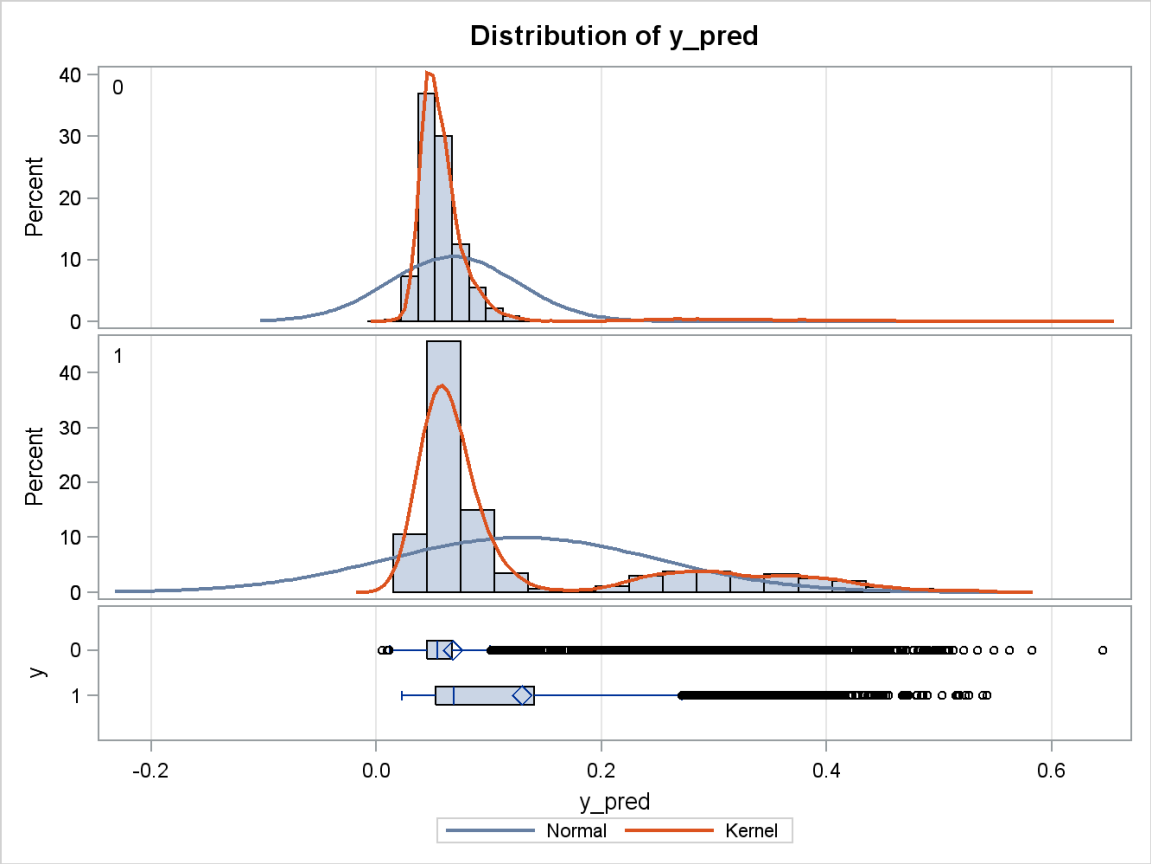

Figure 4: Distribution of predicted outcome for nephropathy (y_pred) stratified by actual outcome (y=0 or 1), for dual beneficiaries (Hypothesis II)

An attempt was made to improve the c-statistic outcome for the models based on an innovative approach. This approach (which will be called 'spline logistic regression')

[38] The original peak is demonstrably higher for y=0 than for y=1, showing lower predicted outcome for y=0 having higher frequency than for y=1.

was based on splitting the data based on residuals obtained from fitting of the original models. Cases with high residuals (poor fit) were separated from cases with low residual (good fit). Then a model was fit for those two cases separately. However, instead of dividing the cases based on their actual residuals, predicted residuals were obtained first. Those predicted residuals were obtained by fitting the original model, but with an outcome indicator showing each case as having high or low residual. This creates a propensity score for each case, or the predicted value for each case of either having a high or low residual. The propensity scores are then split by a chosen percentile[39] value to obtain both data set of predicted low residual (or poor prediction probability) and another data set of predicted high residual (or good prediction probability). Separate models were fit in each case and finally those two sets are combined into a final data set. Performance measures (c-statistic) are obtained for this final data set based on predicted outcomes obtained from the two model fits. This approach is essentially spline logistic regression (or also segmented logistic regression), where the segmentation is based on propensity scores for good and poor predictability. The results of this spline logistic regression approach do not show a significant improvement in c-statistic compared to the original predictive models (in table 38). In general, improvements were in the range of 0.29%-3.42% (based on all the model results). Figure 5 below shows the results for the spline logistic regression approach based on the case presented in Figure 4 (nephropathy for dual beneficiaries for Hypothesis II). The c-statistic for this model improved from .681 (in the original model) to .692 (in the spline logistic regression model)-or a 1.62% improvement. Figure 5 illustrates the improvements, and it appears, for instance, that the additional peak for y=1 is higher compared to that in Figure 4. However, the results are

[39] 80th percentile for good prediction results was chosen in this study

still moderate and this is due to modest improvements based on the c-statistic. Further improvements would be interesting to explore, both with regards to this spline regression approach as well as other approaches beyond spline logistic regression[40]. Other approaches-including other variants of this approach-should be explored to seek to improve performance results for the models in this study.

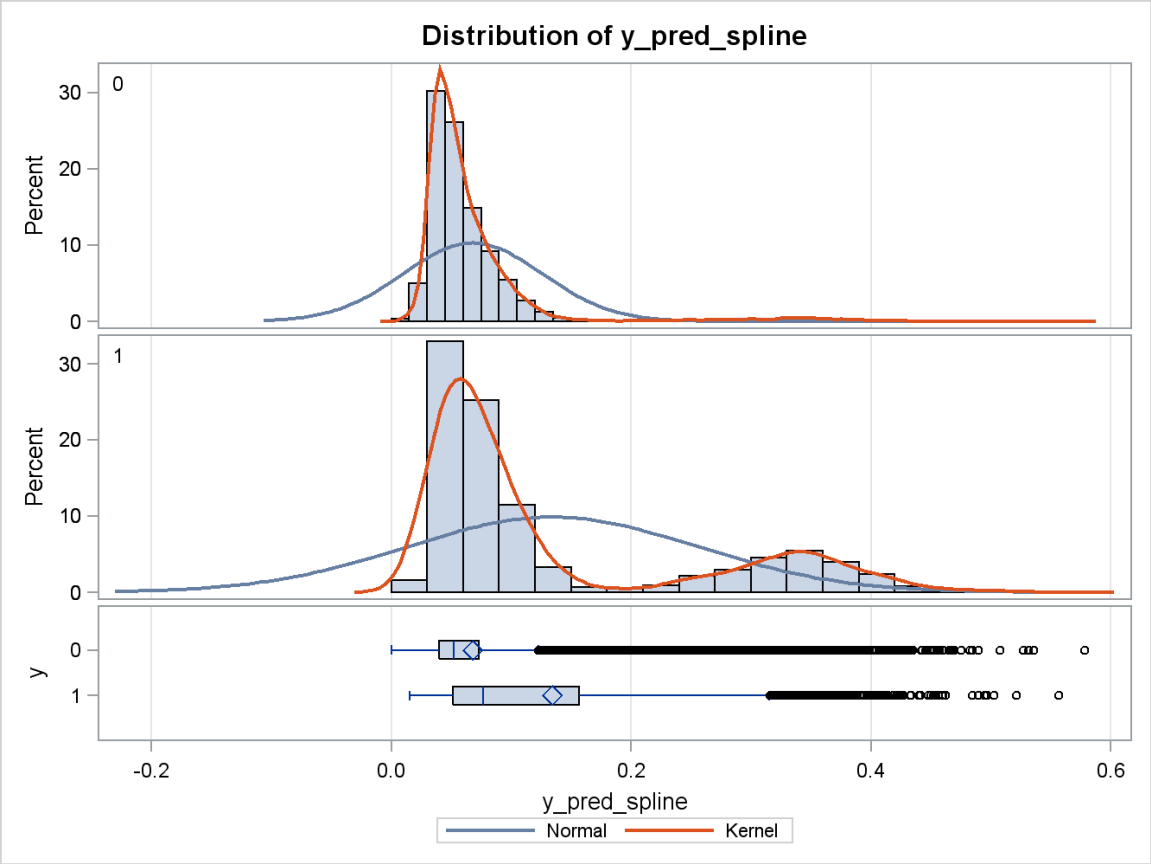

Figure 5: Distribution of predicted outcome for nephropathy (y_pred_spline) stratified by actual outcome (y=0 or 1), for dual beneficiaries (Hypothesis II)

[40] For instance, further breakdown of poor prediction into poor prediction for positive results (y=1) and negative results (y=0) could be explored. This would yield a propensity score model with three outcomes, which would require multinomial logistic regression.

Chapter 6 Conclusion

This dissertation set out to explore factors that influence development of Diabetes complications for Medicare and dual eligible beneficiaries. Three Diabetes complications were of interest in this study: retinopathy, nephropathy and neuropathy. These three complications are the most common and significant microvascular types of complications among Diabetes patients, both from a financial and health standpoint. Results from both predictive and explanatory models were obtained, to gain a better understanding of those factors that influence the development of Diabetes complications. Predictive models were used to study significant factors in development of Diabetes complications among Medicare and dual eligible beneficiaries. Explanatory models were used to explore the three main hypotheses in this dissertation. Each of the hypotheses set out to study the impact that various analytical factors have on development of Diabetes complications in Medicare and dual eligible beneficiaries. These factors included: treatment investment, physician factors and patient cost sharing (or state Medicaid per beneficiary investment for dual eligible beneficiaries).

The results of the predictive models showed the factors that are predictive for each of the Diabetes complications in the study. Odds ratio results for the predictive factors were shown (including a graphical presentation of those odds ratios in the appendix). In general, retinopathy complication resulted in fewer predictive factors than for either nephropathy or neuropathy complications. This pattern was consistent for the results for both non-dual and dual beneficiaries.

The results of the explanatory models set out to answer the three hypothesis that were defined initially in the study. The first hypothesis stated that higher treatment investment would lead to lower rate of complications among Medicare and dual eligible beneficiaries. The results were significant for both retinopathy and neuropathy, but in both cases contrary to the stated hypothesis (i.e., both showed an increasing relation between treatment investment and complication rate among Diabetes beneficiaries, both for non-dual and dual beneficiaries). Results based on HCC and Comorb risk adjustment showed negative significant results for treatment investment for nephropathy (for treatment investments level '2' and higher among non-dual beneficiaries and level '1' and higher among dual beneficiaries[41]). These result show support for the initial hypothesis regarding the impact of treatment investment on nephropathy complication rates among non-dual and dual beneficiaries.

Hypothesis II explored the impact of physician factors on complication rates among beneficiaries. For non-dual beneficiaries, retinopathy and neuropathy both showed higher complication rates among specialist compared to primary care physician (no significant result was found regarding urban vs. rural factor). For nephropathy, rural physicians were shown to have lower complication rates than urban providers. Although no significant results were found regarding primary vs. specialist physician for nephropathy, HCC and Comorb risk adjustment showed lower complication among specialist compared to primary care physicians. For dual beneficiaries, there were two significant outcomes. Retinopathy showed higher complication rates among specialist

[41] Based only on HCC risk adjustment (not Comorb risk adjustment)

(similar to the result obtained for non-dual beneficiaries). Also, neuropathy was shown to have a lower complication rate among rural compared to urban providers (similar to results obtained for nephropathy complication rate among non-dual beneficiaries).

Hypothesis III explored the impact that patient cost sharing had on development of complication rates in beneficiaries. For non-dual beneficiaries, significant results were obtained for retinopathy and neuropathy, both showing a positive relation between patient cost sharing and rate of complications development. Risk adjustment based on HCC and Comorb showed negative significant results for nephropathy, for levels '2' and upward. Also, dips were found for both retinopathy (from levels '2' to '1') and neuropathy (from levels '1' to '0').

For dual beneficiaries, patient cost sharing was based on state Medicaid investment per beneficiary. For retinopathy, there is evidence of a negative relation between state Medicaid investment per beneficiary and complication development. This negative trend is observed for all levels, with the exception of the highest cost level (at level '0'). Nephropathy showed some negative significant results at some of the investment cost levels, mainly from levels '3' and '0', both showing improvement from the lowest cost level '4', with level '0' (highest cost) having the greater outcome improvement. No significant results were obtained for neuropathy complication rate.

In conclusion, the results appear to support some of the hypothesis defined initially in the study, although there are some departures for complication types and among non-dual

compared to dual beneficiaries. With regards to treatment investment, nephropathy appears to be the only complication that shows significant decrease with higher treatment investment levels for beneficiaries (consistent with the initial hypothesis). For physician factors, the conclusions vary. Only nephropathy is consistent with the initial hypothesis that specialist providers have better complication rate outcomes than primary care providers. For urban vs. rural factors, none of the complications showed improvements among urban compared to rural physicians, as was stated in the initial hypothesis. The reverse was found for both nephropathy (among non-dual beneficiaries) and neuropathy (among dual beneficiaries). For patient cost sharing, higher patient cost sharing was found to be associated with higher complication rates among non-dual beneficiaries, for retinopathy and neuropathy (which is contrary to the initial hypothesis). Some evidence of a negative relation was found for nephropathy (using HCC risk adjustment), which is the only complication that supported the initial hypothesis to some extent. For dual beneficiaries, retinopathy (and to an extent nephropathy) showed a significant negative relation with state Medicaid investment per beneficiary. These result support the stated hypothesis that higher state investment leads to lower complication rates among dual eligible beneficiaries.

In addition to the results presented, this study showed the value of the kind of risk adjustment used in a model. HCC and Comorb risk adjustments were used to complement results based on Elixhauser risk adjustment. In general, these were found to have an impact for cost based results (i.e., total treatment investment and patient cost sharing). This could be due to the nature of HCC risk adjustment, which is based on risk

score to predict health cost for Medicare beneficiaries. It is not clear how Comorb would show similar impact as HCC, as it is obtained based on the total number of Elixhauser comorbidities in a beneficiary. However, both measures are obtained as a single measure of risk (compared to a list of variables with Elixhauser risk adjustment). This could be one reason for the similarity in the results between the HCC and Comorb risk adjustment results.

Finally, model performance results show that the best performing models are for nephropathy and neuropathy complications, in comparison to retinopathy complication. In general, retinopathy complication did not have very strong results (which is also evident in the total number of factors obtained in the predictive models). However, for all models, the c-statistics show that improvements could be further made to improve the results obtained in this study. It would be interesting to consider further improvement in the models for future studies, perhaps with more innovative machine learning approaches that have been shown to have high performing results. However, the results in this dissertation shed some light to the factors that influence development of Diabetes complications among Medicare and dual eligible beneficiaries. The results should be helpful in implementing preventive types of care management programs for this population, in order to reduce the risk of Diabetes complications among beneficiaries and improve health outcomes.

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APPENDICES

Appendix A: ICD-9 codes for Diabetes complications: retinopathy, nephropathy and neuropathy

Appendix B: Elixhauser Comorbidities Frequencies, for non-dual and dual beneficiaries in 2010

Appendix C: Medicaid Investment Amount per Beneficiary, in year 2010 by State

Appendix D: Glossary of Model Variables

Appendix E: Base Model Results

Appendix F: Explanatory Model Results

Appendix A: ICD-9 codes for Diabetes complications: retinopathy, nephropathy and neuropathy

Complication	ICD-9 codes
Retinopathy	250.5x, 362.0x, 379.23[42]
Nephropathy	250.4x, 585.xx, 581.81, 583.81
Neuropathy	250.6x, 357.2x, 337.1x

[42] Does not include diagnosis for cataract or glaucoma

Appendix B: Elixhauser Comorbidities Frequencies, for non-dual and dual beneficiaries in 2010

		Non-Duals		Duals	
Comorbidity		**Count**	**Percent**	**Count**	**Percent**
Congestive Heart Failure	no	110,120	86.75%	20,238	79.22%
	yes	16,822	13.25%	5,308	20.78%
Cardiac Arrhythmia	no	97,673	76.94%	19,644	76.90%
	yes	29,269	23.06%	5,902	23.10%
Valvular Disease	no	109,328	86.12%	22,028	86.23%
	yes	17,614	13.88%	3,518	13.77%
Pulmonary Circulation Disorders	no	123,073	96.95%	24,683	96.62%
	yes	3,869	3.05%	863	3.38%
Peripheral Vascular Disorders	no	106,310	83.75%	19,554	76.54%
	yes	20,632	16.25%	5,992	23.46%
Hypertension Uncomplicated	no	14,880	11.72%	2,417	9.46%
	yes	112,062	88.28%	23,129	90.54%
Hypertension complicated	no	115,303	90.83%	22,342	87.46%
	yes	11,639	9.17%	3,204	12.54%
Paralysis	no	125,816	99.11%	25,009	97.90%
	yes	1,126	0.89%	537	2.10%
Other Neurological Disorders	no	120,637	95.03%	23,229	90.93%
	yes	6,305	4.97%	2,317	9.07%
Chronic Pulmonary Disease	no	101,940	80.30%	18,259	71.47%
	yes	25,002	19.70%	7,287	28.53%
Hypothyroidism	no	97,258	76.62%	19,175	75.06%
	yes	29,684	23.38%	6,371	24.94%
Renal Failure	no	121,503	95.72%	24,146	94.52%
	yes	5,439	4.28%	1,400	5.48%
Liver Disease	no	121,368	95.61%	23,918	93.63%
	yes	5,574	4.39%	1,628	6.37%
Peptic Ulcer Disease excluding bleeding	no	125,509	98.87%	25,032	97.99%
	yes	1,433	1.13%	514	2.01%
AIDS/HIV	no	126,879	99.95%	25,496	99.80%
	yes	63	0.05%	50	0.20%
Lymphoma	no	125,487	98.85%	25,349	99.23%
	yes	1,455	1.15%	197	0.77%
Metastatic Cancer	no	125,480	98.85%	25,272	98.93%
	yes	1,462	1.15%	274	1.07%
Solid Tumor without Metastasis	no	109,982	86.64%	23,084	90.36%
	yes	16,960	13.36%	2,462	9.64%

		Non-Duals		Duals	
Comorbidity		**Count**	**Percent**	**Count**	**Percent**
Rheumatoid Arthritis/collagen	no	120,035	94.56%	23,898	93.55%
	yes	6,907	5.44%	1,648	6.45%
Coagulopathy	no	122,227	96.29%	24,545	96.08%
	yes	4,715	3.71%	1,001	3.92%
Obesity	no	117,586	92.63%	23,244	90.99%
	yes	9,356	7.37%	2,302	9.01%
Weight Loss	no	122,505	96.50%	24,113	94.39%
	yes	4,437	3.50%	1,433	5.61%
Fluid and Electrolyte Disorders	no	114,003	89.81%	21,594	84.53%
	yes	12,939	10.19%	3,952	15.47%
Blood Loss Anemia	no	124,942	98.42%	25,014	97.92%
	yes	2,000	1.58%	532	2.08%
Deficiency Anemia	no	115,581	91.05%	22,453	87.89%
	yes	11,361	8.95%	3,093	12.11%
Alcohol Abuse	no	126,247	99.45%	25,306	99.06%
	yes	695	0.55%	240	0.94%
Drug Abuse	no	126,455	99.62%	25,310	99.08%
	yes	487	0.38%	236	0.92%
Psychoses	no	124,640	98.19%	23,789	93.12%
	yes	2,302	1.81%	1,757	6.88%
Depression	no	115,988	91.37%	21,431	83.89%
	yes	10,954	8.63%	4,115	16.11%

Appendix C: Medicaid Investment Amount per Beneficiary, in year 2010 by State

	Unq Ben Count	Tot Medicaid Pd Amt	Amout per Beneficiary
AK	126,754	$1,206,732,274.00	$9,520.27
AL	930,899	$4,041,509,130.00	$4,341.51
AR	772,901	$3,799,386,124.00	$4,915.75
AZ	1,804,818	$9,510,649,340.00	$5,269.59
CA	11,212,114	$34,685,815,704.00	$3,093.60
CO	681,802	$3,300,099,360.00	$4,840.26
CT	663,812	$5,389,954,788.00	$8,119.70
DC	210,607	$1,806,400,158.00	$8,577.11
DE	210,383	$1,342,173,263.00	$6,379.67
FL	3,656,334	$16,130,780,320.00	$4,411.74
GA	1,874,994	$6,969,095,736.00	$3,716.86
HI	288,368	$1,353,091,047.00	$4,692.24
IA	507,553	$3,004,793,099.00	$5,920.16
ID	430,309	$1,235,325,034.00	$2,870.79
IL	2,758,238	$11,645,717,976.00	$4,222.16
IN	1,176,699	$5,752,820,473.00	$4,888.95
KS	363,755	$2,295,014,237.00	$6,309.23
KY	958,732	$5,303,527,296.00	$5,531.81
LA	1,236,843	$5,490,825,433.00	$4,439.39
MA	1,637,405	$11,068,961,061.00	$6,760.06
MD	940,144	$6,837,754,161.00	$7,273.09
ME	329,837	$1,468,070,789.00	$4,450.90
MI	2,219,384	$11,379,559,860.00	$5,127.35
MN	850,556	$7,135,881,709.00	$8,389.67
MO	1,141,253	$6,196,284,095.00	$5,429.37
MS	801,420	$3,363,712,897.00	$4,197.19
MT	126,481	$761,806,453.00	$6,023.09
NC	1,876,395	$9,590,980,459.00	$5,111.39
ND	82,527	$681,780,268.00	$8,261.30
NE	269,370	$1,586,454,999.00	$5,889.50
NH	148,247	$1,008,839,707.00	$6,805.13
NJ	1,229,171	$8,558,223,953.00	$6,962.60
NM	557,415	$2,770,858,831.00	$4,970.91
NV	333,504	$1,300,361,348.00	$3,899.09

	Unq Ben Count	Tot Medicaid Pd Amt	Amout per Beneficiary
NY	5,011,087	$42,723,696,604.00	$8,525.83
OH	2,319,252	$14,450,436,551.00	$6,230.65
OK	852,603	$3,712,748,920.00	$4,354.60
OR	644,068	$3,186,918,628.00	$4,948.11
PA	2,325,603	$15,893,983,198.00	$6,834.35
RI	213,691	$1,574,200,574.00	$7,366.71
SC	953,317	$5,090,193,772.00	$5,339.46
SD	141,863	$777,302,644.00	$5,479.25
TN	1,532,198	$9,060,698,768.00	$5,913.53
TX	4,744,509	$20,718,003,336.00	$4,366.73
UT	369,224	$1,995,359,322.00	$5,404.20
VA	969,496	$5,860,885,947.00	$6,045.29
VT	180,940	$999,752,703.00	$5,525.33
WA	1,330,417	$6,311,836,604.00	$4,744.25
WI	1,230,001	$5,403,498,655.00	$4,393.08
WV	397,094	$2,689,936,243.00	$6,774.05
WY	75,818	$571,684,006.00	$7,540.21

Appendix D: Glossary of Model Variables

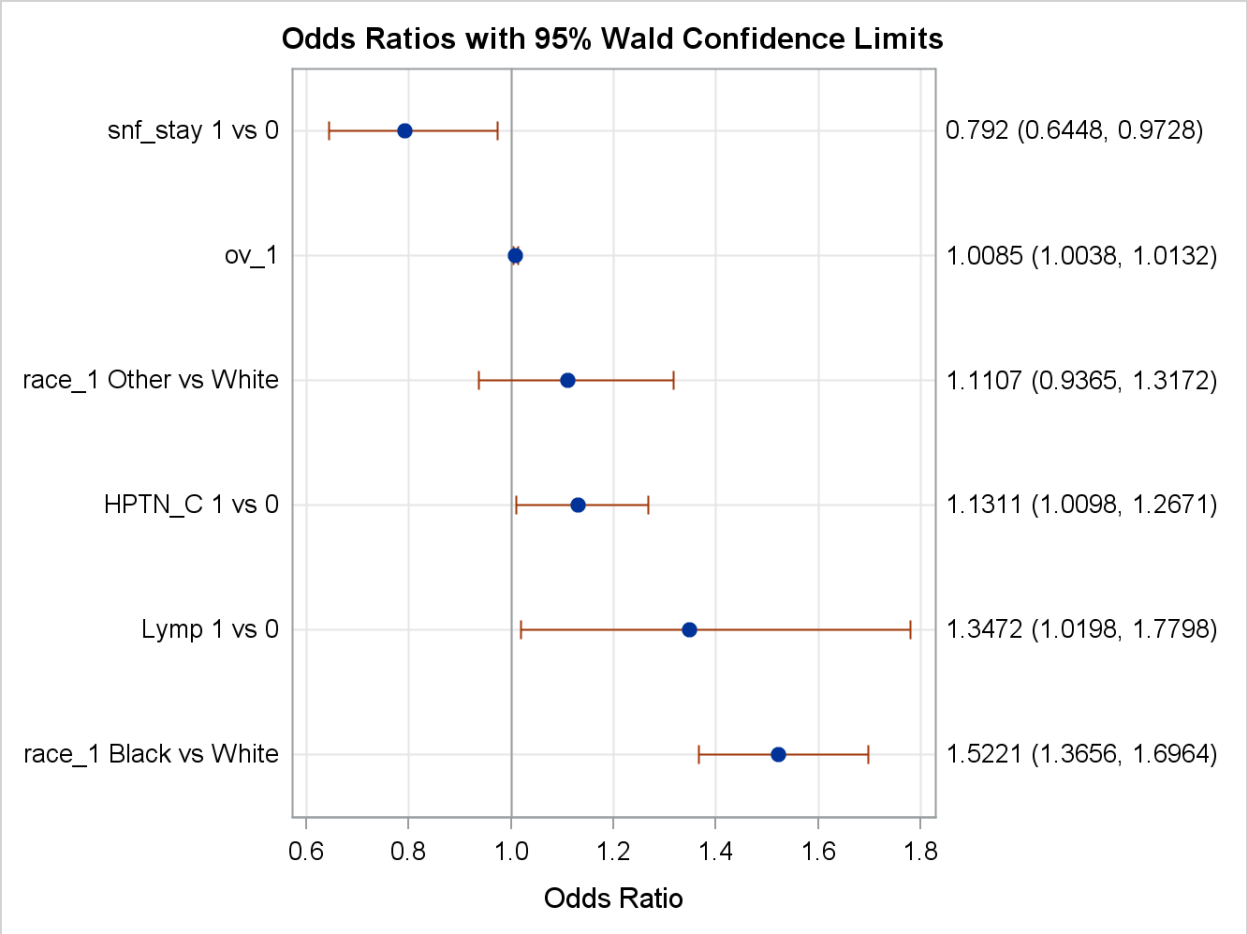
Variable	Description	Values
Socio-Economic Variables		
sex	Sex	M, F
age_grp	Age Group	64 to 69, 70 to 74, 75 to 79, 80 and over
race_1	Race	White, Black, Other
Health Utilization Variables		
ip_tot_stay_1	Inpatient Total Admissions	Amount >=0
op_tot_stay_1	Outpatient Total Admissions	Amount >=0
ov_1	Total Office Visits	Amount >=0
los_1	Total Length of stay	Amount >=0
snf_stay	SNF Admission	yes or no
Comorbidity Factors		
CHF	Congestive Heart Failure	yes or no
Arrhy	Cardiac Arrhythmia	yes or no
VD	Valvular Disease	yes or no
PCD	Pulmonary Circulation Disorders	yes or no
PVD	Peripheral Vascular Disorders	yes or no
HPTN_NC	Hypertension Uncomplicated	yes or no
HPTN_C	Hypertension complicated	yes or no
Para	Paralysis	yes or no
OthND	Other Neurological Disorders	yes or no
COPD	Chronic Pulmonary Disease	yes or no
Hptothy	Hypothyroidism	yes or no
RF	Renal Failure	yes or no
LD	Liver Disease	yes or no
PUD_NB	Peptic Ulcer Disease excluding bleeding	yes or no
HIV	AIDS/HIV	yes or no
Lymp	Lymphoma	yes or no
METS	Metastatic Cancer	yes or no
Tumor	Solid Tumor without Metastasis	yes or no
Rheum_A	Rheumatoid Arthritis/collagen	yes or no
Coag	Coagulopathy	yes or no
Obesity	Obesity	yes or no
WL	Weight Loss	yes or no
Fluid	Fluid and Electrolyte Disorders	yes or no
BLA	Blood Loss Anemia	yes or no
DA	Deficiency Anemia	yes or no
Alcohol	Alcohol Abuse	yes or no

Drug	Drug Abuse	yes or no
Psycho	Psychoses	yes or no
Dep	Depression	yes or no
Analytical Factors		
cost_all	Cost Levels, Total Cost of Treatment	'0' (highest) to '4' (lowest)
cost_all_p	Cost Levels, Total Patient Cost Sharing	'0' (highest) to '4' (lowest)
mcaid_all	Cost Levels, State per Beneficiary Investment	'0' (highest) to '4' (lowest)
prmry_p	Primary vs. Specialist (Primary Care Services)	'1' (primary) or '0' (specialist)
urb	Urban vs. Rural	urban or rural

Appendix E: Base Model Results

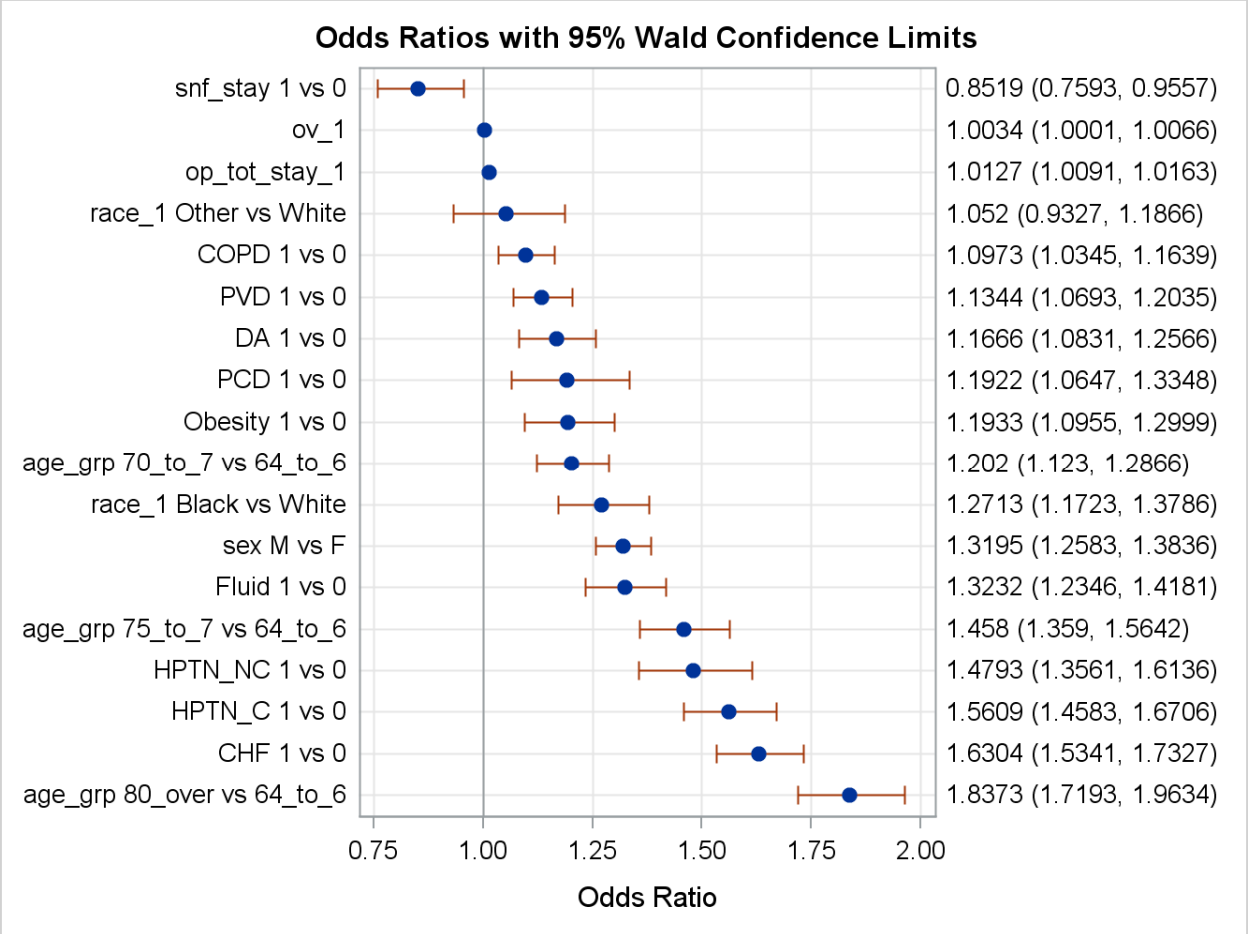
A. Non-Dual Beneficiaries-Retinopathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.7457	0.0294	16201.22	<.0001
race_1	Other	1	0.105	0.087	1.4558	0.2276
race_1	Black	1	0.4201	0.0553	57.6385	<.0001
ov_1		1	0.00842	0.00237	12.5649	0.0004
snf_stay	1	1	-0.2332	0.1049	4.9415	0.0262
HPTN_C	1	1	0.1232	0.0579	4.529	0.0333
Lymp	1	1	0.298	0.1421	4.4003	0.0359



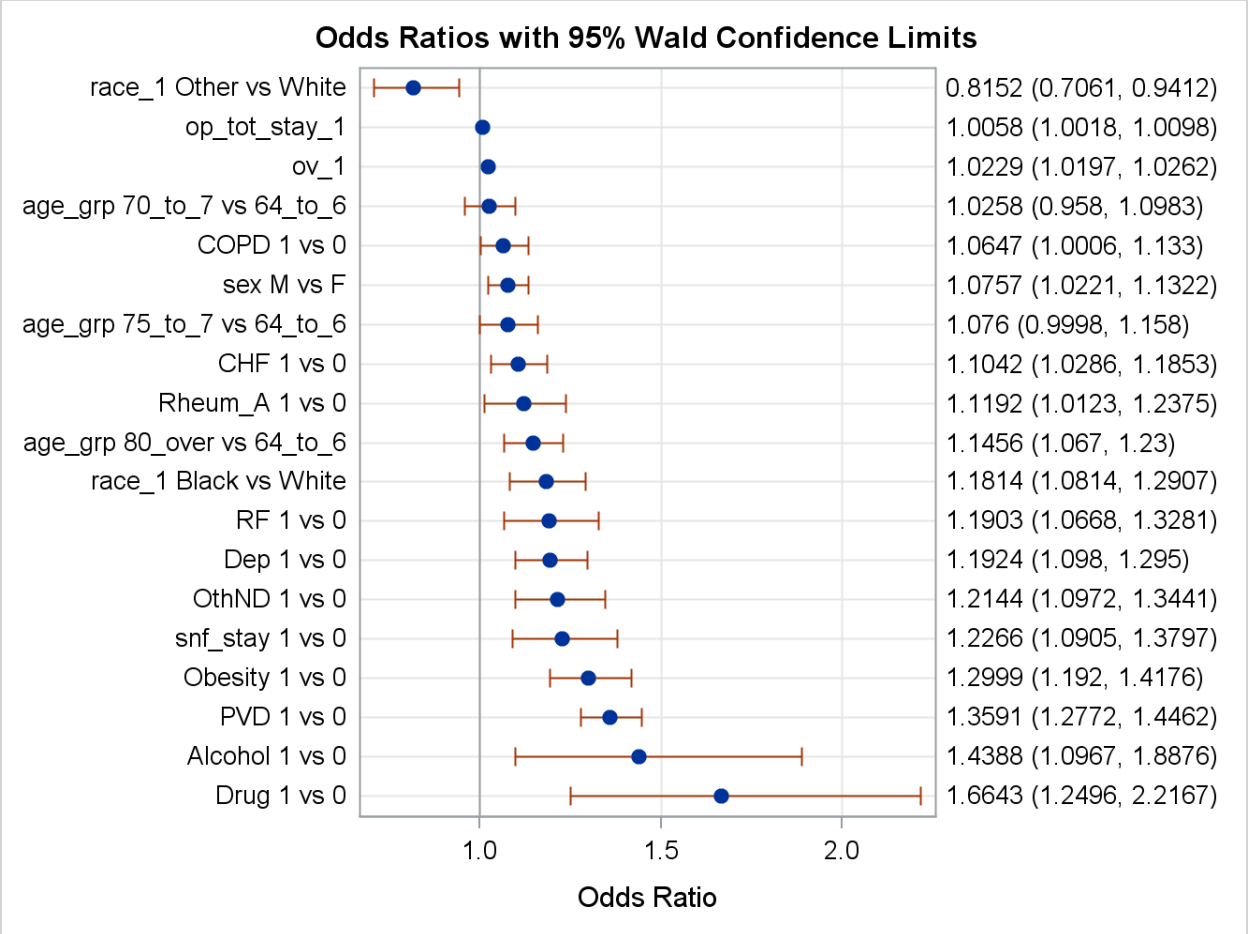
B. Non-Dual Beneficiaries- Nephropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.8961	0.0515	5717.83	<.0001
sex	M	1	0.2772	0.0242	131.0616	<.0001
race_1	Other	1	0.0507	0.0614	0.6811	0.4092
race_1	Black	1	0.24	0.0414	33.6761	<.0001
age_grp	80_over	1	0.6083	0.0339	322.6536	<.0001
age_grp	75_to_7	1	0.3771	0.0359	110.4345	<.0001
age_grp	70_to_7	1	0.184	0.0347	28.1257	<.0001
op_tot_stay_1		1	0.0126	0.00183	47.6859	<.0001
ov_1		1	0.00337	0.00166	4.1337	0.042
snf_stay	1	1	-0.1603	0.0587	7.4704	0.0063
CHF	1	1	0.4888	0.0311	247.7805	<.0001
PCD	1	1	0.1758	0.0577	9.2898	0.0023
PVD	1	1	0.1261	0.0302	17.4745	<.0001
HPTN_NC	1	1	0.3916	0.0443	77.9467	<.0001
HPTN_C	1	1	0.4452	0.0347	164.8844	<.0001
COPD	1	1	0.0929	0.03	9.5502	0.002
Obesity	1	1	0.1767	0.0436	16.403	<.0001
Fluid	1	1	0.28	0.0353	62.8034	<.0001
DA	1	1	0.1541	0.0379	16.5391	<.0001


Odds Ratios with 95% Wald Confidence Limits
snf_stay 1 vs 0
ov_1
op_tot_stay_1
race_1 Other vs White
COPD 1 vs 0
PVD 1 vs 0
DA 1 vs 0
PCD 1 vs 0
Obesity 1 vs 0
age_grp 70_to_7 vs 64_to_6
race_1 Black vs White
sex M vs F
Fluid 1 vs 0
age_grp 75_to_7 vs 64_to_6
HPTN_NC 1 vs 0
HPTN_C 1 vs 0
CHF 1 vs 0
age_grp 80_over vs 64_to_6
0.8519 (0.7593, 0.9557)
1.0034 (1.0001, 1.0066)
1.0127 (1.0091, 1.0163)
1.052 (0.9327, 1.1866)
1.0973 (1.0345, 1.1639)
1.1344 (1.0693, 1.2035)
1.1666 (1.0831, 1.2566)
1.1922 (1.0647, 1.3348)
1.1933 (1.0955, 1.2999)
1.202 (1.123, 1.2866)
1.2713 (1.1723, 1.3786)
1.3195 (1.2583, 1.3836)
1.3232 (1.2346, 1.4181)
1.458 (1.359, 1.5642)
1.4793 (1.3561, 1.6136)
1.5609 (1.4583, 1.6706)
1.6304 (1.5341, 1.7327)
1.8373 (1.7193, 1.9634)
0.75
1.00
1.25
1.50
1.75
2.00
Odds Ratio

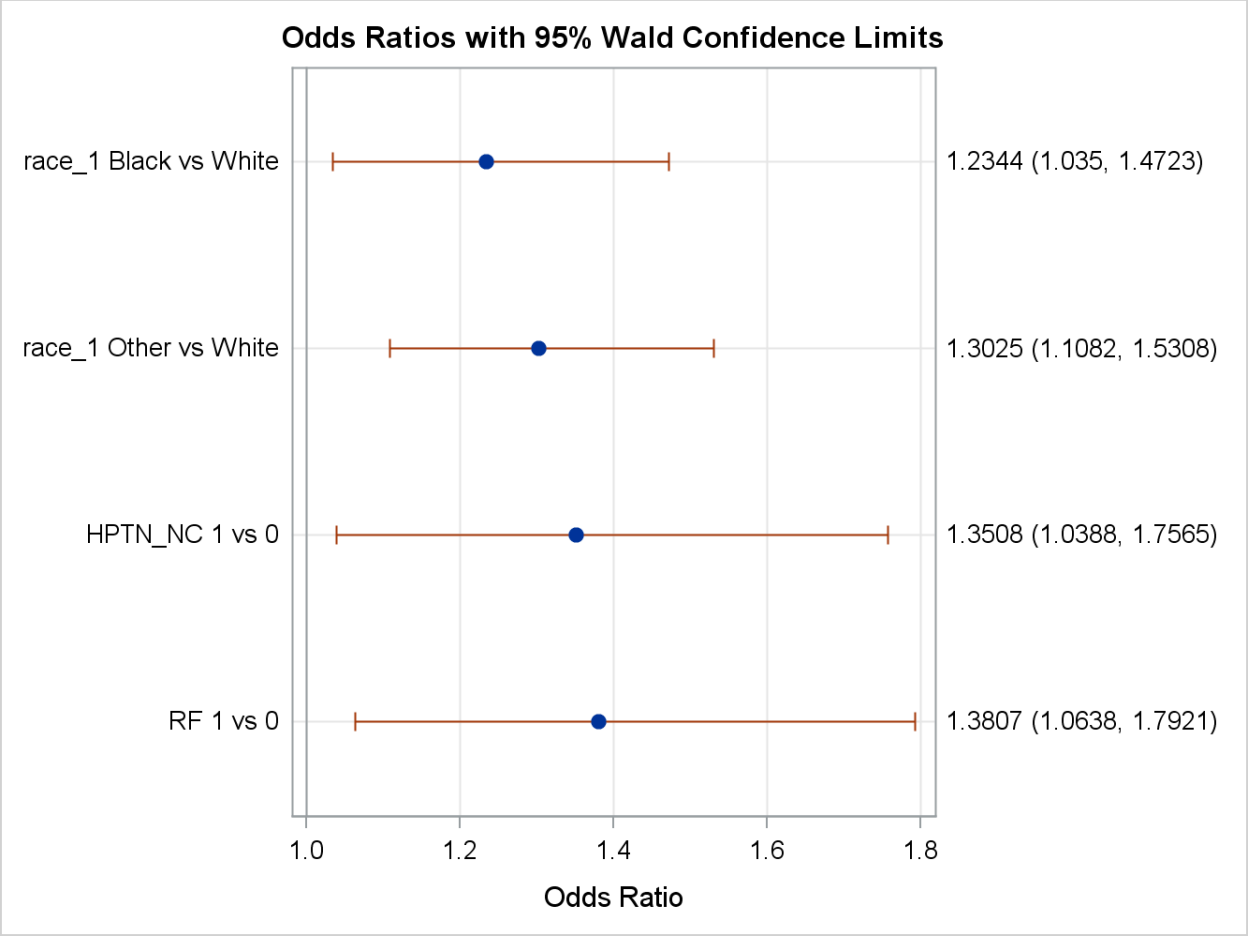
C. Non-Dual Beneficiaries- Neuropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.4332	0.0334	10594.43	<.0001
sex	M	1	0.073	0.0261	7.8132	0.0052
race_1	Other	1	-0.2043	0.0733	7.7656	0.0053
race_1	Black	1	0.1667	0.0451	13.6521	0.0002
age_grp	80_over	1	0.1359	0.0363	14.0465	0.0002
age_grp	75_to_7	1	0.0732	0.0375	3.8239	0.0505
age_grp	70_to_7	1	0.0254	0.0349	0.5321	0.4657
op_tot_stay_1		1	0.00576	0.00203	8.0122	0.0046
ov_1		1	0.0227	0.00162	195.7852	<.0001
snf_stay	1	1	0.2042	0.06	11.5798	0.0007
CHF	1	1	0.0991	0.0362	7.51	0.0061
PVD	1	1	0.3068	0.0317	93.696	<.0001
OthND	1	1	0.1942	0.0518	14.0663	0.0002
COPD	1	1	0.0627	0.0317	3.9136	0.0479
RF	1	1	0.1742	0.0559	9.7171	0.0018
Rheum_A	1	1	0.1127	0.0512	4.8343	0.0279
Obesity	1	1	0.2623	0.0442	35.18	<.0001
Alcohol	1	1	0.3638	0.1385	6.8959	0.0086
Drug	1	1	0.5094	0.1462	12.1394	0.0005
Dep	1	1	0.176	0.0421	17.4914	<.0001


Odds Ratios with 95% Wald Confidence Limits
race_1 Other vs White
op_tot_stay_1
ov_1
age_grp 70_to_7 vs 64_to_6
COPD 1 vs 0
sex M vs F
age_grp 75_to_7 vs 64_to_6
CHF 1 vs 0
Rheum_A 1 vs 0
age_grp 80_over vs 64_to_6
race_1 Black vs White
RF 1 vs 0
Dep 1 vs 0
OthND 1 vs 0
snf_stay 1 vs 0
Obesity 1 vs 0
PVD 1 vs 0
Alcohol 1 vs 0
Drug 1 vs 0
0.8152 (0.7061, 0.9412)
1.0058 (1.0018, 1.0098)
1.0229 (1.0197, 1.0262)
1.0258 (0.958, 1.0983)
1.0647 (1.0006, 1.133)
1.0757 (1.0221, 1.1322)
1.076 (0.9998, 1.158)
1.1042 (1.0286, 1.1853)
1.1192 (1.0123, 1.2375)
1.1456 (1.067, 1.23)
1.1814 (1.0814, 1.2907)
1.1903 (1.0668, 1.3281)
1.1924 (1.098, 1.295)
1.2144 (1.0972, 1.3441)
1.2266 (1.0905, 1.3797)
1.2999 (1.192, 1.4176)
1.3591 (1.2772, 1.4462)
1.4388 (1.0967, 1.8876)
1.6643 (1.2496, 2.2167)
1.0
1.5
2.0
Odds Ratio

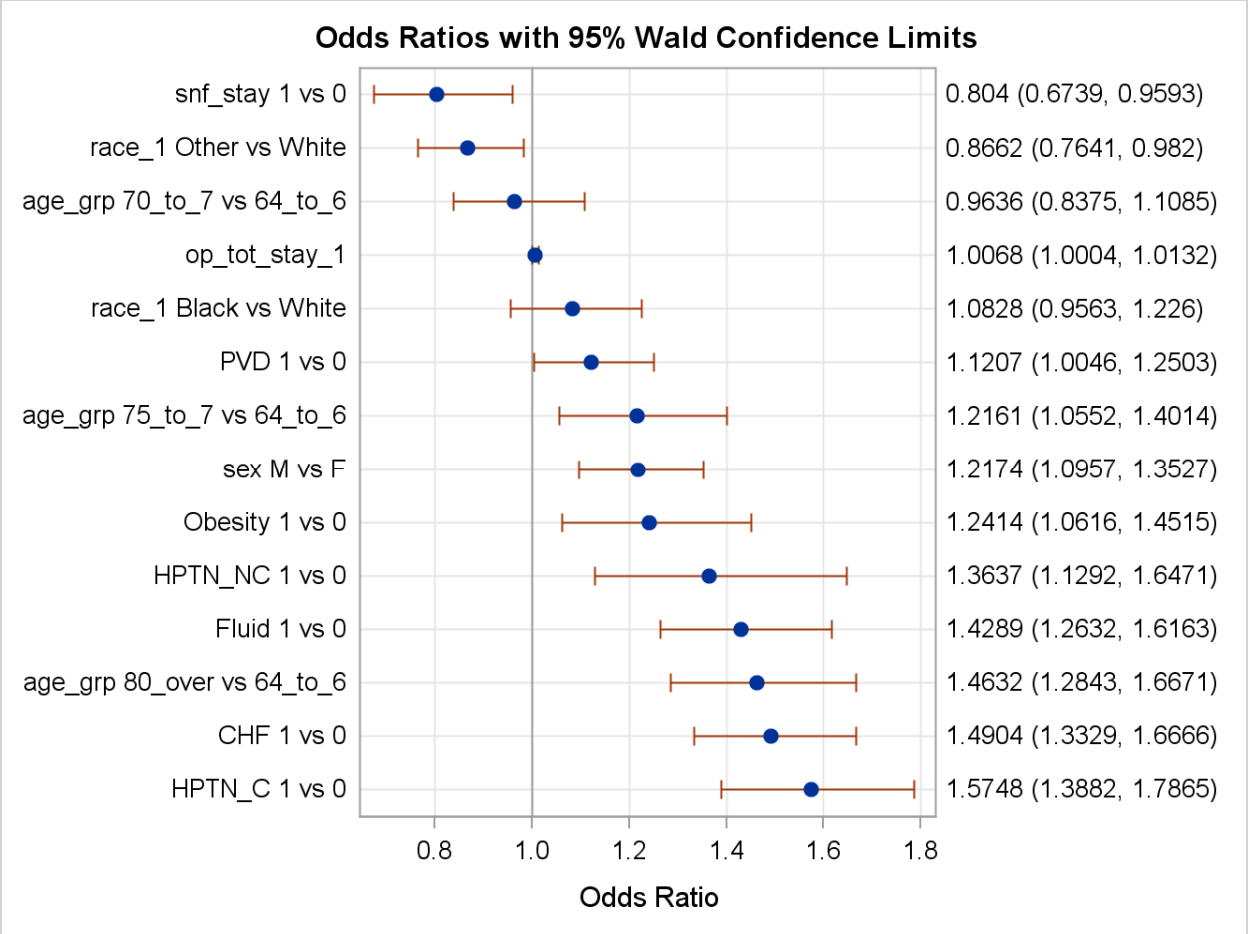
D. Dual Beneficiaries- Retinopathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.7482	0.1324	801.5499	<.0001
race_1	Other	1	0.2643	0.0824	10.2822	0.0013
race_1	Black	1	0.2106	0.0899	5.4868	0.0192
HPTN_NC	1	1	0.3007	0.134	5.0355	0.0248
RF	1	1	0.3226	0.1331	5.8779	0.0153



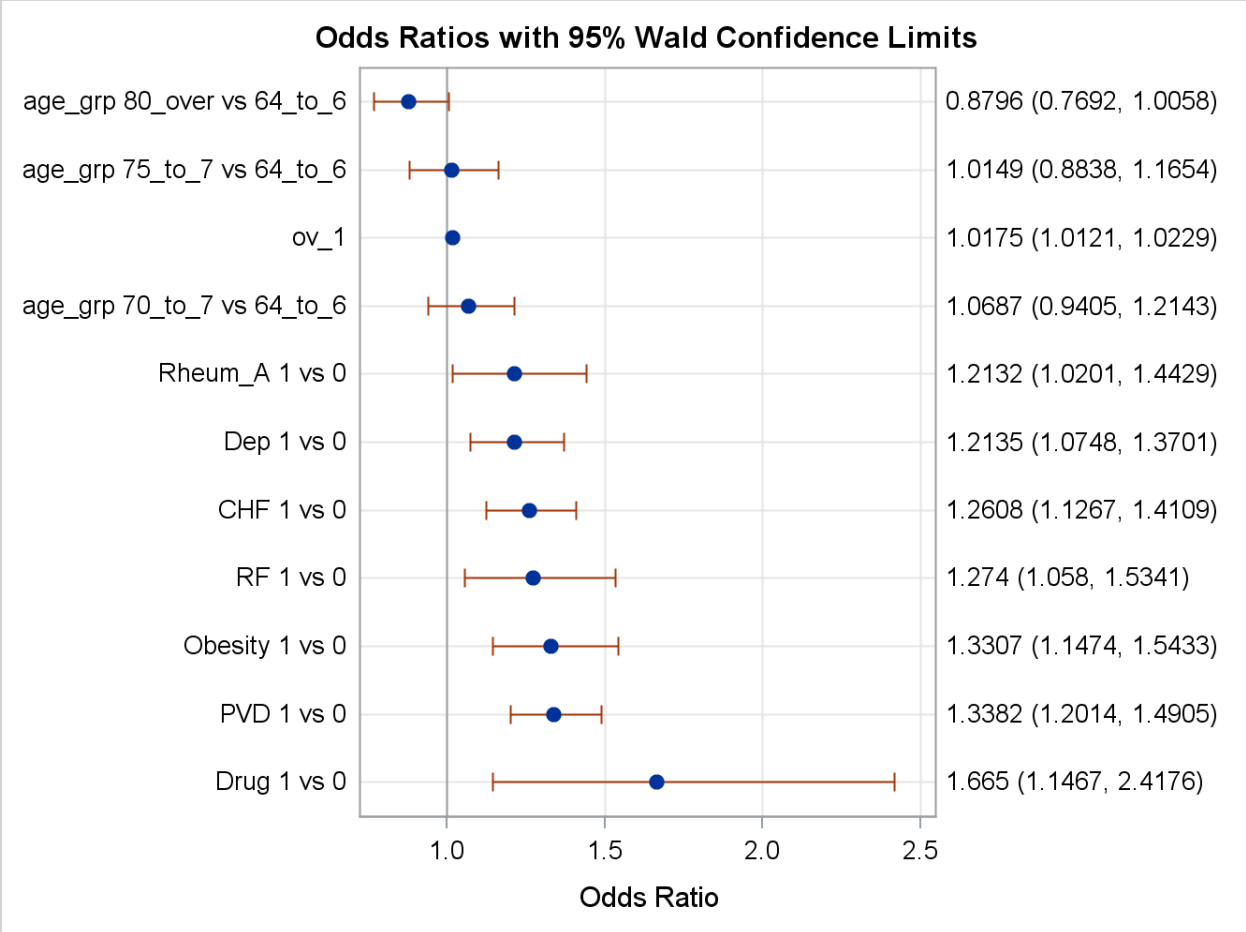
E. Dual Beneficiaries- Nephropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.333	0.1077	958.3138	<.0001
sex	M	1	0.1967	0.0538	13.3906	0.0003
race_1	Other	1	-0.1436	0.064	5.0349	0.0248
race_1	Black	1	0.0795	0.0634	1.5737	0.2097
age_grp	80_over	1	0.3806	0.0666	32.7075	<.0001
age_grp	75_to_7	1	0.1956	0.0724	7.3053	0.0069
age_grp	70_to_7	1	-0.0371	0.0715	0.2694	0.6037
op_tot_stay_1		1	0.00674	0.00325	4.3106	0.0379
snf_stay	1	1	-0.2181	0.0901	5.865	0.0154
CHF	1	1	0.3991	0.057	49.0149	<.0001
PVD	1	1	0.114	0.0558	4.1707	0.0411
HPTN_NC	1	1	0.3102	0.0963	10.3764	0.0013
HPTN_C	1	1	0.4541	0.0643	49.8123	<.0001
Obesity	1	1	0.2162	0.0798	7.3404	0.0067
Fluid	1	1	0.3569	0.0629	32.2196	<.0001


Odds Ratios with 95% Wald Confidence Limits
snf_stay 1 vs 0
race_1 Other vs White
age_grp 70_to_7 vs 64_to_6
op_tot_stay_1
race_1 Black vs White
PVD 1 vs 0
age_grp 75_to_7 vs 64_to_6
sex M vs F
Obesity 1 vs 0
HPTN_NC 1 vs 0
Fluid 1 vs 0
age_grp 80_over vs 64_to_6
CHF 1 vs 0
HPTN_C 1 vs 0
0.804 (0.6739, 0.9593)
0.8662 (0.7641, 0.982)
0.9636 (0.8375, 1.1085)
1.0068 (1.0004, 1.0132)
1.0828 (0.9563, 1.226)
1.1207 (1.0046, 1.2503)
1.2161 (1.0552, 1.4014)
1.2174 (1.0957, 1.3527)
1.2414 (1.0616, 1.4515)
1.3637 (1.1292, 1.6471)
1.4289 (1.2632, 1.6163)
1.4632 (1.2843, 1.6671)
1.4904 (1.3329, 1.6666)
1.5748 (1.3882, 1.7865)
0.8
1.0
1.2
1.4
1.6
1.8
Odds Ratio

F. Dual Beneficiaries- Neuropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-2.9273	0.0543	2908.764	<.0001
age_grp	80_over	1	-0.1283	0.0684	3.519	0.0607
age_grp	75_to_7	1	0.0148	0.0705	0.0438	0.8343
age_grp	70_to_7	1	0.0664	0.0652	1.0392	0.308
ov_1		1	0.0173	0.00271	40.9632	<.0001
CHF	1	1	0.2318	0.0574	16.3135	<.0001
PVD	1	1	0.2913	0.055	28.0431	<.0001
RF	1	1	0.2422	0.0948	6.5265	0.0106
Rheum_A	1	1	0.1933	0.0885	4.7731	0.0289
Obesity	1	1	0.2857	0.0756	14.269	0.0002
Drug	1	1	0.5098	0.1903	7.1791	0.0074
Dep	1	1	0.1935	0.0619	9.761	0.0018



Appendix F: Explanatory Model Results

I. Hypothesis 1

A. Non-Dual Beneficiaries-Retinopathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.8873	0.0742	2746.562	<.0001
cost_all	3	1	1.39E-01	6.01E-02	5.3298	0.021
cost_all	2	1	0.2908	0.0603	23.2304	<.0001
cost_all	1	1	0.3065	0.064	22.9067	<.0001
cost_all	0	1	0.3168	0.0793	15.9744	<.0001
sex	M	1	-0.0562	0.0369	2.3182	0.1279
race_1	Other	1	0.1099	0.0872	1.5857	0.2079
race_1	Black	1	0.4035	0.0561	51.6578	<.0001
age_grp	80_over	1	-0.0921	0.0519	3.146	0.0761
age_grp	75_to_7	1	0.00652	0.0512	0.0162	0.8988
age_grp	70_to_7	1	0.0697	0.046	2.2908	0.1301
ip_tot_stay_1		1	-0.00787	0.0496	0.0251	0.8741
op_tot_stay_1		1	0.000218	0.00335	0.0042	0.9482
ov_1		1	0.00503	0.00298	2.8457	0.0916
snf_stay	1	1	-0.2971	0.117	6.4439	0.0111
los_1		1	0.00254	0.00528	0.2325	0.6297
CHF	1	1	0.1093	0.0557	3.8419	0.05
Arrhy	1	1	-0.0123	0.0469	0.0682	0.794
VD	1	1	-0.1228	0.0553	4.9232	0.0265
PCD	1	1	-0.00363	0.1083	0.0011	0.9733
PVD	1	1	0.0663	0.0481	1.9022	0.1678
HPTN_NC	1	1	0.0426	0.0575	0.5479	0.4592
HPTN_C	1	1	0.0944	0.0595	2.5142	0.1128
Para	1	1	-0.0199	0.1909	0.0109	0.917
OthND	1	1	-0.0391	0.0851	0.2106	0.6463
COPD	1	1	-0.1455	0.0482	9.0988	0.0026
Hptothy	1	1	-0.0296	0.043	0.4721	0.492
RF	1	1	0.1074	0.0829	1.6814	0.1947
LD	1	1	-0.0401	0.0866	0.2145	0.6433
PUD_NB	1	1	-0.0878	0.1671	0.276	0.5994
HIV	1	1	0.8234	0.5177	2.5295	0.1117
Lymp	1	1	0.2908	0.1429	4.1383	0.0419
METS	1	1	-0.1517	0.1785	0.7217	0.3956
Tumor	1	1	-0.1075	0.0552	3.7954	0.0514
Rheum_A	1	1	-0.2432	0.0847	8.2498	0.0041
Coag	1	1	-0.1686	0.1001	2.8353	0.0922
Obesity	1	1	-0.0247	0.0675	0.1342	0.7142
WL	1	1	0.075	0.0934	0.6449	0.422

Fluid	1	1	0.0699	0.0607	1.325	0.2497
BLA	1	1	0.1952	0.1293	2.2814	0.1309
DA	1	1	0.0357	0.0618	0.3339	0.5634
Alcohol	1	1	0.1315	0.225	0.3414	0.559
Drug	1	1	-0.2891	0.3218	0.8069	0.3691
Psycho	1	1	-0.2218	0.1505	2.1724	0.1405
Dep	1	1	-0.019	0.0649	0.0854	0.7701

B. Non-Dual Beneficiaries- Nephropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.9255	0.0576	4643.804	<.0001
cost_all	3	1	7.62E-02	4.24E-02	3.2364	0.072
cost_all	2	1	-0.00055	0.0437	0.0002	0.9899
cost_all	1	1	0.0556	0.0451	1.52	0.2176
cost_all	0	1	0.00436	0.0539	0.0065	0.9355
sex	M	1	0.2371	0.0257	85.117	<.0001
race_1	Other	1	0.0633	0.0629	1.0117	0.3145
race_1	Black	1	0.2236	0.0427	27.3631	<.0001
age_grp	80_over	1	0.5436	0.0351	239.9502	<.0001
age_grp	75_to_7	1	0.3347	0.0368	82.5151	<.0001
age_grp	70_to_7	1	0.1679	0.0354	22.4946	<.0001
ip_tot_stay_1		1	-0.0471	0.0304	2.3964	0.1216
op_tot_stay_1		1	0.00767	0.00201	14.5057	0.0001
ov_1		1	0.00265	0.00195	1.8454	0.1743
snf_stay	1	1	-0.1695	0.0677	6.2749	0.0122
los_1		1	0.00104	0.00315	0.1091	0.7412
CHF	1	1	0.404	0.0339	142.308	<.0001
Arrhy	1	1	0.0429	0.0309	1.9268	0.1651
VD	1	1	0.00731	0.0349	0.044	0.8339
PCD	1	1	0.1531	0.0614	6.2197	0.0126
PVD	1	1	0.1171	0.0314	13.8595	0.0002
HPTN_NC	1	1	0.3344	0.0451	54.9281	<.0001
HPTN_C	1	1	0.1834	0.037	24.6033	<.0001
Para	1	1	-0.1451	0.1282	1.281	0.2577
OthND	1	1	-0.0621	0.0552	1.2633	0.261
COPD	1	1	0.1029	0.0311	10.9294	0.0009
Hptothy	1	1	-0.0284	0.0298	0.9115	0.3397
RF	1	1	2.0007	0.0337	3529.091	<.0001
LD	1	1	-0.0875	0.0604	2.097	0.1476
PUD_NB	1	1	-0.0145	0.1066	0.0184	0.892
HIV	1	1	-0.2656	0.6101	0.1895	0.6633
Lymp	1	1	0.1418	0.1033	1.884	0.1699
METS	1	1	0.1055	0.1064	0.9823	0.3216
Tumor	1	1	0.0395	0.036	1.2063	0.2721
Rheum_A	1	1	-0.0297	0.0534	0.3096	0.5779
Coag	1	1	-0.036	0.0596	0.3648	0.5459
Obesity	1	1	0.1633	0.0451	13.1256	0.0003
WL	1	1	0.0447	0.0609	0.5396	0.4626

Fluid	1	1	0.1581	0.0386	16.8076	<.0001
BLA	1	1	0.0891	0.0875	1.0368	0.3086
DA	1	1	0.1302	0.0399	10.6327	0.0011
Alcohol	1	1	0.2024	0.1462	1.9161	0.1663
Drug	1	1	-0.00186	0.1869	0.0001	0.992
Psycho	1	1	0.0101	0.0856	0.0139	0.9061
Dep	1	1	0.0615	0.0436	1.9954	0.1578

C. Non-Dual Beneficiaries- Neuropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.5852	0.0566	4006.947	<.0001
cost_all	3	1	1.64E-01	4.84E-02	11.3918	0.0007
cost_all	2	1	0.3321	0.0476	48.7446	<.0001
cost_all	1	1	0.4593	0.0485	89.643	<.0001
cost_all	0	1	0.5335	0.0567	88.5906	<.0001
sex	M	1	0.0916	0.0269	11.5485	0.0007
race_1	Other	1	-0.1996	0.0734	7.3875	0.0066
race_1	Black	1	0.177	0.0455	15.1436	<.0001
age_grp	80_over	1	0.1354	0.0367	13.5999	0.0002
age_grp	75_to_7	1	0.0732	0.0376	3.7816	0.0518
age_grp	70_to_7	1	0.0254	0.035	0.528	0.4675
ip_tot_stay_1		1	-0.0595	0.0305	3.809	0.051
op_tot_stay_1		1	0.0025	0.00217	1.3216	0.2503
ov_1		1	0.0184	0.00186	97.3392	<.0001
snf_stay	1	1	0.1183	0.0659	3.2279	0.0724
los_1		1	0.00646	0.00295	4.7999	0.0285
CHF	1	1	0.0827	0.0382	4.7031	0.0301
Arrhy	1	1	-0.0317	0.0327	0.938	0.3328
VD	1	1	-0.0728	0.0375	3.7661	0.0523
PCD	1	1	-0.0402	0.0698	0.3319	0.5646
PVD	1	1	0.266	0.032	69.1537	<.0001
HPTN_NC	1	1	-0.0401	0.0419	0.9146	0.3389
HPTN_C	1	1	0.0321	0.0423	0.5767	0.4476
Para	1	1	-0.0156	0.1196	0.0171	0.8961
OthND	1	1	0.1434	0.0531	7.3026	0.0069
COPD	1	1	0.0435	0.0324	1.8027	0.1794
Hptothy	1	1	-0.0142	0.0308	0.2133	0.6442
RF	1	1	0.1704	0.0565	9.097	0.0026
LD	1	1	0.0362	0.0585	0.3837	0.5356
PUD_NB	1	1	-0.0268	0.1106	0.0587	0.8085
HIV	1	1	0.193	0.5188	0.1383	0.71
Lymp	1	1	-0.2617	0.1223	4.5771	0.0324
METS	1	1	-0.0174	0.1149	0.0229	0.8797
Tumor	1	1	-0.1688	0.0395	18.2632	<.0001
Rheum_A	1	1	0.0841	0.0513	2.6885	0.1011
Coag	1	1	-0.1318	0.0648	4.1311	0.0421
Obesity	1	1	0.2342	0.0444	27.8205	<.0001
WL	1	1	-0.0818	0.066	1.5338	0.2155

Fluid	1	1	-0.013	0.0422	0.0942	0.7589
BLA	1	1	-0.00436	0.095	0.0021	0.9634
DA	1	1	-0.0118	0.0435	0.0737	0.786
Alcohol	1	1	0.3128	0.1396	5.0217	0.025
Drug	1	1	0.4587	0.1464	9.8147	0.0017
Psycho	1	1	0.1019	0.0842	1.4627	0.2265
Dep	1	1	0.1398	0.0425	10.8379	0.001

D. Dual Beneficiaries-Retinopathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.7948	0.1633	539.9824	<.0001
cost_all	3	1	1.54E-01	1.19E-01	1.6853	0.1942
cost_all	2	1	0.4295	0.1185	13.1448	0.0003
cost_all	1	1	0.3535	0.1299	7.4062	0.0065
cost_all	0	1	0.6318	0.158	15.9847	<.0001
sex	M	1	-0.03	0.0801	0.1399	0.7084
race_1	Other	1	0.2455	0.0855	8.2484	0.0041
race_1	Black	1	0.2041	0.092	4.9261	0.0265
age_grp	80_over	1	-0.1298	0.0986	1.7325	0.1881
age_grp	75_to_7	1	-0.0955	0.1031	0.8577	0.3544
age_grp	70_to_7	1	0.0537	0.0924	0.3377	0.5612
ip_tot_stay_1		1	-0.0735	0.0936	0.6159	0.4326
op_tot_stay_1		1	-0.00067	0.00538	0.0154	0.9011
ov_1		1	-0.00337	0.00533	0.4003	0.5269
snf_stay	1	1	-0.0221	0.1583	0.0195	0.8889
los_1		1	-0.00994	0.0112	0.7865	0.3752
CHF	1	1	0.0542	0.0954	0.323	0.5698
Arrhy	1	1	-0.1251	0.0937	1.7828	0.1818
VD	1	1	0.0727	0.1049	0.4796	0.4886
PCD	1	1	0.2075	0.1972	1.1069	0.2928
PVD	1	1	0.0488	0.0846	0.3322	0.5643
HPTN_NC	1	1	0.2555	0.1358	3.5413	0.0599
HPTN_C	1	1	0.0677	0.1055	0.4116	0.5212
Para	1	1	0.3317	0.2169	2.3395	0.1261
OthND	1	1	0.085	0.1263	0.4534	0.5007
COPD	1	1	-0.3248	0.0873	13.8546	0.0002
Hptothy	1	1	0.024	0.0821	0.0856	0.7698
RF	1	1	0.3485	0.1369	6.4789	0.0109
LD	1	1	0.034	0.1428	0.0566	0.8119
PUD_NB	1	1	-0.2004	0.2672	0.5626	0.4532
HIV	1	1	0.1005	0.7268	0.0191	0.8901
Lymp	1	1	-0.3511	0.458	0.5876	0.4433
METS	1	1	0.3519	0.3295	1.1412	0.2854
Tumor	1	1	-0.2817	0.1367	4.2449	0.0394
Rheum_A	1	1	-0.1021	0.1474	0.4794	0.4887
Coag	1	1	-0.1027	0.1902	0.2915	0.5892
Obesity	1	1	0.0482	0.1201	0.1608	0.6884
WL	1	1	-0.505	0.1916	6.9503	0.0084

Fluid	1	1	-0.1287	0.11	1.3686	0.2421
BLA	1	1	-0.3175	0.2871	1.2232	0.2687
DA	1	1	0.0732	0.1071	0.4674	0.4942
Alcohol	1	1	0.2427	0.3319	0.5346	0.4647
Drug	1	1	0.2145	0.3296	0.4235	0.5152
Psycho	1	1	-0.2294	0.1576	2.1166	0.1457
Dep	1	1	0.0657	0.0985	0.4448	0.5048

E. Dual Beneficiaries-Nephropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.3549	0.1197	784.9242	<.0001
cost_all	3	1	7.53E-02	8.59E-02	0.7684	0.3807
cost_all	2	1	0.0334	0.089	0.141	0.7073
cost_all	1	1	0.018	0.0935	0.037	0.8475
cost_all	0	1	0.0199	0.1145	0.0302	0.8621
sex	M	1	0.139	0.0565	6.0494	0.0139
race_1	Other	1	-0.1346	0.0664	4.1098	0.0426
race_1	Black	1	0.0794	0.0664	1.4308	0.2316
age_grp	80_over	1	0.3046	0.0694	19.2466	<.0001
age_grp	75_to_7	1	0.1566	0.0745	4.4163	0.0356
age_grp	70_to_7	1	-0.0724	0.0732	0.9773	0.3229
ip_tot_stay_1		1	-0.032	0.0519	0.3808	0.5372
op_tot_stay_1		1	0.00262	0.00359	0.5331	0.4653
ov_1		1	0.00132	0.00361	0.1331	0.7152
snf_stay	1	1	-0.2128	0.1076	3.9117	0.048
los_1		1	-0.00341	0.00513	0.4412	0.5066
CHF	1	1	0.3059	0.0633	23.3547	<.0001
Arrhy	1	1	0.0883	0.063	1.9643	0.1611
VD	1	1	-0.00116	0.0735	0.0003	0.9874
PCD	1	1	0.1124	0.1269	0.7849	0.3757
PVD	1	1	0.097	0.0591	2.6965	0.1006
HPTN_NC	1	1	0.2385	0.0988	5.8281	0.0158
HPTN_C	1	1	0.2008	0.0696	8.3224	0.0039
Para	1	1	-0.1335	0.1823	0.5364	0.4639
OthND	1	1	0.0201	0.0888	0.051	0.8214
COPD	1	1	0.0606	0.0584	1.0772	0.2993
Hptothy	1	1	0.0213	0.0587	0.1313	0.7171
RF	1	1	1.9015	0.0671	803.4205	<.0001
LD	1	1	0.184	0.0989	3.4652	0.0627
PUD_NB	1	1	-0.1566	0.1814	0.7451	0.388
HIV	1	1	-1.3788	1.0244	1.8115	0.1783
Lymp	1	1	-0.0251	0.2702	0.0086	0.9261
METS	1	1	0.061	0.2326	0.0689	0.793
Tumor	1	1	-0.00793	0.0872	0.0083	0.9276
Rheum_A	1	1	-0.2397	0.1074	4.9785	0.0257
Coag	1	1	-0.0678	0.1226	0.3062	0.58
Obesity	1	1	0.1816	0.0833	4.7539	0.0292
WL	1	1	-0.0697	0.1097	0.4041	0.525

Fluid	1	1	0.2368	0.07	11.4272	0.0007
BLA	1	1	0.1085	0.1587	0.4677	0.494
DA	1	1	0.0456	0.0748	0.3722	0.5418
Alcohol	1	1	-0.0497	0.2599	0.0366	0.8482
Drug	1	1	0.3153	0.2335	1.8229	0.177
Psycho	1	1	-0.3069	0.1103	7.7391	0.0054
Dep	1	1	-0.0543	0.072	0.5694	0.4505

F. Dual Beneficiaries-Neuropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.1278	0.1144	748.0233	<.0001
cost_all	3	1	3.57E-01	9.46E-02	14.2529	0.0002
cost_all	2	1	0.5794	0.0934	38.4477	<.0001
cost_all	1	1	0.739	0.0962	59.0534	<.0001
cost_all	0	1	0.9622	0.1124	73.226	<.0001
sex	M	1	-0.0177	0.0562	0.0992	0.7528
race_1	Other	1	-0.078	0.0627	1.5437	0.2141
race_1	Black	1	-0.1216	0.0686	3.1448	0.0762
age_grp	80_over	1	-0.1513	0.0704	4.6184	0.0316
age_grp	75_to_7	1	0.00523	0.0714	0.0054	0.9417
age_grp	70_to_7	1	0.0612	0.0656	0.8708	0.3507
ip_tot_stay_1		1	-0.0286	0.0526	0.2961	0.5863
op_tot_stay_1		1	-0.0035	0.00356	0.9645	0.3261
ov_1		1	0.00861	0.0032	7.2107	0.0072
snf_stay	1	1	-0.1715	0.1032	2.7638	0.0964
los_1		1	-0.00745	0.00604	1.5218	0.2173
CHF	1	1	0.1716	0.0627	7.492	0.0062
Arrhy	1	1	-0.1265	0.0625	4.1014	0.0428
VD	1	1	-0.0677	0.0717	0.8914	0.3451
PCD	1	1	0.00395	0.1283	0.0009	0.9755
PVD	1	1	0.2315	0.0561	17.0378	<.0001
HPTN_NC	1	1	-0.0705	0.088	0.6419	0.423
HPTN_C	1	1	0.0579	0.071	0.6652	0.4147
Para	1	1	-0.0642	0.1666	0.1484	0.7
OthND	1	1	0.00421	0.086	0.0024	0.961
COPD	1	1	0.0274	0.0556	0.2431	0.622
Hptothy	1	1	-0.0504	0.0571	0.7797	0.3772
RF	1	1	0.2285	0.0964	5.6192	0.0178
LD	1	1	-0.1323	0.099	1.7854	0.1815
PUD_NB	1	1	-0.0482	0.1639	0.0864	0.7688
HIV	1	1	0.3087	0.4783	0.4166	0.5187
Lymp	1	1	0.1191	0.2459	0.2347	0.6281
METS	1	1	-0.11	0.236	0.2174	0.6411
Tumor	1	1	-0.1515	0.0868	3.0476	0.0809
Rheum_A	1	1	0.1472	0.0888	2.7476	0.0974
Coag	1	1	0.1472	0.1123	1.7171	0.1901
Obesity	1	1	0.2484	0.0765	10.5491	0.0012
WL	1	1	-0.0883	0.1075	0.675	0.4113

Fluid	1	1	0.1061	0.0693	2.3398	0.1261
BLA	1	1	-0.2681	0.1762	2.315	0.1281
DA	1	1	0.0215	0.0728	0.0874	0.7675
Alcohol	1	1	-0.1146	0.252	0.2068	0.6493
Drug	1	1	0.484	0.1915	6.3885	0.0115
Psycho	1	1	-0.3555	0.1084	10.7588	0.001

II. Hypothesis 2

A. Non-Dual Beneficiaries-Retinopathy

Parameter			DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept			1	-3.7893	0.0694	2979.882	<.0001
prmry_p	0		1	8.83E-02	4.41E-02	4.0109	0.0452
urb	rural		1	-0.0305	0.0525	0.3374	0.5613
prmry_p*urb	0	rural	1	0.1228	0.0858	2.0463	0.1526
sex	M		1	-0.0678	0.0371	3.3308	0.068
race_1	Other		1	0.0931	0.0888	1.0988	0.2945
race_1	Black		1	0.3977	0.0569	48.8418	<.0001
age_grp	80_over		1	-0.0751	0.0522	2.0727	0.15
age_grp	75_to_7		1	0.0172	0.0515	0.1121	0.7378
age_grp	70_to_7		1	0.0731	0.0463	2.4917	0.1145
ip_tot_stay_1			1	0.015	0.0457	0.1083	0.7421
op_tot_stay_1			1	0.00199	0.00332	0.3615	0.5477
ov_1			1	0.00889	0.00283	9.8505	0.0017
snf_stay	1		1	-0.2753	0.1166	5.5698	0.0183
los_1			1	0.00122	0.0054	0.0506	0.8219
CHF	1		1	0.1126	0.056	4.0336	0.0446
Arrhy	1		1	0.00446	0.0471	0.009	0.9245
VD	1		1	-0.1133	0.0556	4.1541	0.0415
PCD	1		1	-0.018	0.1089	0.0272	0.869
PVD	1		1	0.0878	0.0481	3.3333	0.0679
HPTN_NC	1		1	0.0573	0.0578	0.9806	0.3221
HPTN_C	1		1	0.1019	0.0597	2.9116	0.0879
Para	1		1	-0.00466	0.191	0.0006	0.9805
OthND	1		1	-0.022	0.0853	0.0666	0.7964
COPD	1		1	-0.1321	0.0484	7.4435	0.0064
Hptothy	1		1	-0.0217	0.0431	0.2539	0.6143
RF	1		1	0.1067	0.0832	1.6444	0.1997
LD	1		1	-0.0192	0.0867	0.049	0.8247
PUD_NB	1		1	-0.0736	0.1672	0.1939	0.6597
HIV	1		1	0.8647	0.518	2.7873	0.095
Lymp	1		1	0.273	0.1443	3.5801	0.0585
METS	1		1	-0.1715	0.1785	0.9231	0.3367
Tumor	1		1	-0.0994	0.0554	3.2206	0.0727
Rheum_A	1		1	-0.2457	0.0851	8.3466	0.0039
Coag	1		1	-0.1732	0.1003	2.9807	0.0843
Obesity	1		1	-0.0144	0.0678	0.0452	0.8316
WL	1		1	0.0879	0.0936	0.8822	0.3476
Fluid	1		1	0.0892	0.0609	2.1428	0.1432

BLA	1	1	0.2026	0.1294	2.4526	0.1173
DA	1	1	0.0487	0.062	0.6177	0.4319
Alcohol	1	1	0.1069	0.2303	0.2157	0.6424
Drug	1	1	-0.2906	0.3219	0.8153	0.3665
Psycho	1	1	-0.1959	0.1507	1.6899	0.1936
Dep	1	1	0.000794	0.0651	0.0001	0.9903

B. Non-Dual Beneficiaries-Nephropathy

Parameter			DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept			1	-3.8604	0.0546	4999.326	<.0001
prmry_p	0		1	-1.04E-02	3.03E-02	0.1178	0.7315
urb	rural		1	-0.1182	0.0367	10.3623	0.0013
prmry_p*urb	0	rural	1	0.037	0.0612	0.3661	0.5451
sex	M		1	0.2365	0.0258	83.9462	<.0001
race_1	Other		1	0.0609	0.0634	0.922	0.3369
race_1	Black		1	0.2033	0.0432	22.1081	<.0001
age_grp	80_over		1	0.5409	0.0352	236.1332	<.0001
age_grp	75_to_7		1	0.3326	0.037	80.932	<.0001
age_grp	70_to_7		1	0.1695	0.0355	22.791	<.0001
ip_tot_stay_1			1	-0.0543	0.0281	3.7429	0.053
op_tot_stay_1			1	0.00914	0.00201	20.6556	<.0001
ov_1			1	0.00163	0.00191	0.7337	0.3917
snf_stay	1		1	-0.187	0.067	7.7833	0.0053
los_1			1	0.00104	0.00313	0.1097	0.7404
CHF	1		1	0.4076	0.0338	145.0286	<.0001
Arrhy	1		1	0.0432	0.0309	1.9555	0.162
VD	1		1	0.00195	0.0349	0.0031	0.9555
PCD	1		1	0.1486	0.0615	5.8336	0.0157
PVD	1		1	0.1161	0.0313	13.7374	0.0002
HPTN_NC	1		1	0.3378	0.0454	55.2995	<.0001
HPTN_C	1		1	0.1807	0.037	23.8043	<.0001
Para	1		1	-0.1511	0.1282	1.3889	0.2386
OthND	1		1	-0.0613	0.0552	1.2336	0.2667
COPD	1		1	0.1064	0.0311	11.6645	0.0006
Hptothy	1		1	-0.0302	0.0298	1.0259	0.3111
RF	1		1	2.0025	0.0338	3510.897	<.0001
LD	1		1	-0.0958	0.0605	2.5075	0.1133
PUD_NB	1		1	-0.0146	0.1066	0.0188	0.8909
HIV	1		1	-0.2695	0.6114	0.1944	0.6593
Lymp	1		1	0.1467	0.1034	2.0132	0.1559
METS	1		1	0.0987	0.1063	0.8613	0.3534
Tumor	1		1	0.0376	0.0361	1.0837	0.2979
Rheum_A	1		1	-0.0337	0.0535	0.3959	0.5292
Coag	1		1	-0.0421	0.0597	0.4986	0.4801
Obesity	1		1	0.1635	0.0451	13.1455	0.0003
WL	1		1	0.0474	0.0609	0.6066	0.4361
Fluid	1		1	0.161	0.0386	17.4315	<.0001

BLA	1	1	0.0881	0.0875	1.0138	0.314
DA	1	1	0.1285	0.04	10.3386	0.0013
Alcohol	1	1	0.1981	0.1463	1.834	0.1757
Drug	1	1	-0.00036	0.1868	0	0.9985
Psycho	1	1	0.0146	0.0856	0.0292	0.8643
Dep	1	1	0.06	0.0436	1.891	0.1691

C. Non-Dual Beneficiaries-Neuropathy

Parameter			DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept			1	-3.4417	0.0511	4531.255	<.0001
prmry_p	0		1	1.19E-01	3.13E-02	14.5139	0.0001
urb	rural		1	-0.0454	0.0389	1.3605	0.2434
prmry_p*urb	0	rural	1	0.00346	0.0632	0.003	0.9563
sex	M		1	0.0785	0.027	8.4278	0.0037
race_1	Other		1	-0.2026	0.0738	7.5255	0.0061
race_1	Black		1	0.1703	0.0459	13.7986	0.0002
age_grp	80_over		1	0.1536	0.0368	17.4126	<.0001
age_grp	75_to_7		1	0.0841	0.0378	4.9673	0.0258
age_grp	70_to_7		1	0.0314	0.035	0.8049	0.3696
ip_tot_stay_1			1	-0.00058	0.0283	0.0004	0.9836
op_tot_stay_1			1	0.00675	0.00213	10.0217	0.0015
ov_1			1	0.0229	0.0018	161.4299	<.0001
snf_stay	1		1	0.1608	0.0661	5.9258	0.0149
los_1			1	0.00387	0.00305	1.612	0.2042
CHF	1		1	0.1034	0.0384	7.2552	0.0071
Arrhy	1		1	-0.013	0.0329	0.1548	0.694
VD	1		1	-0.0573	0.0377	2.3084	0.1287
PCD	1		1	-0.0547	0.0703	0.6064	0.4361
PVD	1		1	0.3006	0.032	88.3443	<.0001
HPTN_NC	1		1	-0.00506	0.0422	0.0144	0.9044
HPTN_C	1		1	0.0421	0.0425	0.9832	0.3214
Para	1		1	0.0107	0.12	0.008	0.9289
OthND	1		1	0.1611	0.0535	9.0838	0.0026
COPD	1		1	0.0654	0.0325	4.0442	0.0443
Hptothy	1		1	-0.00663	0.0309	0.0461	0.83
RF	1		1	0.1684	0.0567	8.8297	0.003
LD	1		1	0.0577	0.0587	0.9658	0.3257
PUD_NB	1		1	-0.00058	0.111	0	0.9958
HIV	1		1	0.2064	0.5192	0.1581	0.6909
Lymp	1		1	-0.2481	0.1226	4.093	0.0431
METS	1		1	-0.0261	0.1152	0.0514	0.8207
Tumor	1		1	-0.1512	0.0397	14.5225	0.0001
Rheum_A	1		1	0.0977	0.0514	3.6092	0.0575
Coag	1		1	-0.1357	0.0651	4.3426	0.0372
Obesity	1		1	0.2522	0.0445	32.1295	<.0001
WL	1		1	-0.0678	0.0663	1.0469	0.3062
Fluid	1		1	0.00793	0.0426	0.0347	0.8521

BLA	1	1	-0.00177	0.0957	0.0003	0.9852
DA	1	1	0.00299	0.0437	0.0047	0.9455
Alcohol	1	1	0.3479	0.1399	6.1882	0.0129
Drug	1	1	0.4702	0.147	10.2356	0.0014
Psycho	1	1	0.1262	0.0848	2.2139	0.1368
Dep	1	1	0.1659	0.0427	15.1224	0.0001

D. Dual Beneficiaries-Retinopathy

Parameter			DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept			1	-3.651	0.1585	530.934	<.0001
prmry_p	0		1	1.77E-01	8.67E-02	4.1553	0.0415
urb	rural		1	-0.1611	0.1049	2.3568	0.1247
prmry_p*urb	0	rural	1	-0.2681	0.1898	1.9951	0.1578
sex	M		1	-0.0194	0.0804	0.058	0.8097
race_1	Other		1	0.2008	0.0877	5.2488	0.022
race_1	Black		1	0.1886	0.0928	4.1269	0.0422
age_grp	80_over		1	-0.1118	0.0994	1.2653	0.2606
age_grp	75_to_7		1	-0.0848	0.1041	0.6641	0.4151
age_grp	70_to_7		1	0.0758	0.093	0.6658	0.4145
ip_tot_stay_1			1	0.0151	0.0865	0.0305	0.8615
op_tot_stay_1			1	0.00543	0.0053	1.0485	0.3059
ov_1			1	0.000983	0.00509	0.0372	0.847
snf_stay	1		1	0.097	0.1554	0.3901	0.5323
los_1			1	-0.0119	0.0112	1.1327	0.2872
CHF	1		1	0.0967	0.0958	1.02	0.3125
Arrhy	1		1	-0.1282	0.0947	1.8333	0.1757
VD	1		1	0.0907	0.1054	0.7405	0.3895
PCD	1		1	0.1899	0.1976	0.9236	0.3365
PVD	1		1	0.0774	0.0847	0.8341	0.3611
HPTN_NC	1		1	0.2896	0.1375	4.4332	0.0352
HPTN_C	1		1	0.0804	0.1057	0.5789	0.4467
Para	1		1	0.3756	0.2177	2.9756	0.0845
OthND	1		1	0.1233	0.1268	0.9447	0.3311
COPD	1		1	-0.2877	0.0878	10.7356	0.0011
Hptothy	1		1	0.0284	0.0826	0.1183	0.7309
RF	1		1	0.3488	0.1372	6.4629	0.011
LD	1		1	0.0387	0.1431	0.0733	0.7866
PUD_NB	1		1	-0.1862	0.2673	0.4851	0.4861
HIV	1		1	0.1176	0.7288	0.026	0.8718
Lymp	1		1	-0.3449	0.4578	0.5677	0.4512
METS	1		1	0.38	0.3295	1.3297	0.2489
Tumor	1		1	-0.2766	0.1371	4.0678	0.0437
Rheum_A	1		1	-0.0905	0.1488	0.37	0.543
Coag	1		1	-0.113	0.1908	0.351	0.5536
Obesity	1		1	0.0363	0.1215	0.0892	0.7652
WL	1		1	-0.4884	0.1919	6.4764	0.0109
Fluid	1		1	-0.0925	0.1107	0.6981	0.4034

BLA	1	1	-0.3186	0.2876	1.2277	0.2679
DA	1	1	0.0776	0.1077	0.5194	0.4711
Alcohol	1	1	0.2731	0.3326	0.6741	0.4116
Drug	1	1	0.2452	0.33	0.5523	0.4574
Psycho	1	1	-0.2432	0.1608	2.2856	0.1306
Dep	1	1	0.1031	0.0989	1.0874	0.297

E. Dual Beneficiaries-Nephropathy

Parameter			DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept			1	-3.3081	0.1165	806.8484	<.0001
prmry_p	0		1	-1.38E-02	6.54E-02	0.0446	0.8328
urb	rural		1	0.00221	0.0716	0.0009	0.9754
prmry_p*urb	0	rural	1	-0.00224	0.125	0.0003	0.9857
sex	M		1	0.1352	0.0569	5.6466	0.0175
race_1	Other		1	-0.1261	0.068	3.4378	0.0637
race_1	Black		1	0.0857	0.0669	1.6419	0.2001
age_grp	80_over		1	0.3	0.0697	18.5417	<.0001
age_grp	75_to_7		1	0.1522	0.0748	4.1356	0.042
age_grp	70_to_7		1	-0.0865	0.0737	1.3777	0.2405
ip_tot_stay_1			1	-0.0391	0.0483	0.6544	0.4185
op_tot_stay_1			1	0.0036	0.00363	0.9874	0.3204
ov_1			1	0.00105	0.00351	0.0901	0.764
snf_stay	1		1	-0.2238	0.1043	4.6028	0.0319
los_1			1	-0.00305	0.00505	0.3645	0.546
CHF	1		1	0.3088	0.0631	23.9749	<.0001
Arrhy	1		1	0.0913	0.063	2.1015	0.1472
VD	1		1	-0.00369	0.0735	0.0025	0.9599
PCD	1		1	0.1129	0.1269	0.7923	0.3734
PVD	1		1	0.0934	0.0589	2.5138	0.1129
HPTN_NC	1		1	0.233	0.0998	5.4518	0.0195
HPTN_C	1		1	0.1893	0.0698	7.3593	0.0067
Para	1		1	-0.1594	0.1844	0.7467	0.3875
OthND	1		1	0.0154	0.0889	0.03	0.8624
COPD	1		1	0.0624	0.0584	1.1435	0.2849
Hptothy	1		1	0.0298	0.0588	0.2571	0.6121
RF	1		1	1.8984	0.0673	794.5444	<.0001
LD	1		1	0.1853	0.0989	3.5098	0.061
PUD_NB	1		1	-0.1582	0.1813	0.7614	0.3829
HIV	1		1	-1.3338	1.0264	1.6889	0.1937
Lymp	1		1	-0.025	0.2702	0.0086	0.9263
METS	1		1	0.0596	0.2323	0.0659	0.7974
Tumor	1		1	-0.0151	0.0876	0.0297	0.8632
Rheum_A	1		1	-0.2471	0.1078	5.2589	0.0218
Coag	1		1	-0.0677	0.1226	0.3046	0.581
Obesity	1		1	0.1768	0.0835	4.4826	0.0342
WL	1		1	-0.0709	0.1097	0.4172	0.5183
Fluid	1		1	0.2401	0.0698	11.8281	0.0006

BLA	1	1	0.1091	0.1587	0.4723	0.4919
DA	1	1	0.0478	0.0748	0.4088	0.5226
Alcohol	1	1	-0.0368	0.2605	0.02	0.8876
Drug	1	1	0.3134	0.2335	1.801	0.1796
Psycho	1	1	-0.3006	0.1105	7.4073	0.0065
Dep	1	1	-0.0606	0.0721	0.7062	0.4007

F. Dual Beneficiaries-Neuropathy

Parameter			DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept			1	-2.8439	0.1045	740.9165	<.0001
prmry_p	0		1	2.68E-02	6.21E-02	0.1858	0.6665
urb	rural		1	-0.1734	0.0734	5.5779	0.0182
prmry_p*urb	0	rural	1	0.0536	0.1254	0.183	0.6688
sex	M		1	-0.0397	0.0566	0.4906	0.4837
race_1	Other		1	-0.1071	0.0642	2.7844	0.0952
race_1	Black		1	-0.1382	0.0692	3.9823	0.046
age_grp	80_over		1	-0.107	0.0708	2.2838	0.1307
age_grp	75_to_7		1	0.0305	0.072	0.1799	0.6715
age_grp	70_to_7		1	0.0904	0.0659	1.881	0.1702
ip_tot_stay_1			1	0.0702	0.0494	2.0252	0.1547
op_tot_stay_1			1	0.0033	0.00354	0.8704	0.3508
ov_1			1	0.0153	0.00308	24.8887	<.0001
snf_stay	1		1	-0.0451	0.1025	0.1936	0.6599
los_1			1	-0.0103	0.00621	2.7654	0.0963
CHF	1		1	0.2259	0.0632	12.7771	0.0004
Arrhy	1		1	-0.1049	0.0634	2.7367	0.0981
VD	1		1	-0.0413	0.0724	0.3252	0.5685
PCD	1		1	-0.0445	0.1298	0.1175	0.7317
PVD	1		1	0.2907	0.0563	26.6752	<.0001
HPTN_NC	1		1	0.00166	0.0891	0.0003	0.9851
HPTN_C	1		1	0.0907	0.0713	1.6173	0.2035
Para	1		1	-0.00549	0.1678	0.0011	0.9739
OthND	1		1	0.0533	0.0869	0.3757	0.5399
COPD	1		1	0.0826	0.056	2.1779	0.14
Hptothy	1		1	-0.0413	0.0574	0.5169	0.4721
RF	1		1	0.2241	0.0969	5.3508	0.0207
LD	1		1	-0.1078	0.0995	1.1749	0.2784
PUD_NB	1		1	-0.014	0.1643	0.0072	0.9322
HIV	1		1	0.3914	0.4803	0.6639	0.4152
Lymp	1		1	0.1697	0.246	0.4758	0.4903
METS	1		1	-0.0625	0.2371	0.0696	0.792
Tumor	1		1	-0.1256	0.0876	2.0566	0.1516
Rheum_A	1		1	0.1976	0.0891	4.9157	0.0266
Coag	1		1	0.1645	0.113	2.1199	0.1454
Obesity	1		1	0.279	0.0767	13.2495	0.0003
WL	1		1	-0.0606	0.108	0.3151	0.5746
Fluid	1		1	0.156	0.0701	4.9469	0.0261

BLA	1	1	-0.2691	0.1772	2.3052	0.1289
DA	1	1	0.0437	0.0732	0.3563	0.5506
Alcohol	1	1	-0.0437	0.253	0.0299	0.8628
Drug	1	1	0.5257	0.1922	7.4838	0.0062
Psycho	1	1	-0.3269	0.1097	8.8748	0.0029
Dep	1	1	0.1923	0.0653	8.6618	0.0032

I. Hypothesis 3

A. Non-Dual Beneficiaries-Retinopathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.8646	0.0741	2723.547	<.0001
Cost_all_p	3	1	1.03E-01	5.99E-02	2.9314	0.0869
Cost_all_p	2	1	0.2603	0.0601	18.7818	<.0001
Cost_all_p	1	1	0.2699	0.0634	18.1254	<.0001
Cost_all_p	0	1	0.3453	0.0791	19.0744	<.0001
sex	M	1	-0.0595	0.0369	2.5926	0.1074
race_1	Other	1	0.1084	0.0872	1.5453	0.2138
race_1	Black	1	0.4052	0.0562	52.0719	<.0001
age_grp	80_over	1	-0.0844	0.0519	2.6398	0.1042
age_grp	75_to_7	1	0.011	0.0512	0.0462	0.8298
age_grp	70_to_7	1	0.072	0.046	2.4461	0.1178
ip_tot_stay_1		1	-0.0294	0.0492	0.3584	0.5494
op_tot_stay_1		1	-0.00034	0.0034	0.0101	0.9199
ov_1		1	0.00472	0.003	2.4822	0.1151
snf_stay	1	1	-0.3093	0.1167	7.029	0.008
los_1		1	0.00292	0.00524	0.3101	0.5776
CHF	1	1	0.1131	0.0557	4.1236	0.0423
Arrhy	1	1	-0.0107	0.0469	0.0522	0.8193
VD	1	1	-0.1242	0.0554	5.0322	0.0249
PCD	1	1	-0.0038	0.1082	0.0012	0.972
PVD	1	1	0.0653	0.0481	1.8443	0.1744
HPTN_NC	1	1	0.0416	0.0575	0.5231	0.4695
HPTN_C	1	1	0.0947	0.0595	2.5294	0.1117
Para	1	1	-0.0188	0.1908	0.0097	0.9215
OthND	1	1	-0.0393	0.0851	0.2131	0.6443
COPD	1	1	-0.1441	0.0483	8.9196	0.0028
Hptothy	1	1	-0.0257	0.043	0.356	0.5508
RF	1	1	0.1103	0.0829	1.7698	0.1834
LD	1	1	-0.0398	0.0866	0.2106	0.6463
PUD_NB	1	1	-0.0908	0.1671	0.2953	0.5868
HIV	1	1	0.8473	0.5177	2.6779	0.1017
Lymp	1	1	0.2891	0.1429	4.0904	0.0431
METS	1	1	-0.1599	0.1784	0.8027	0.3703
Tumor	1	1	-0.1089	0.0552	3.8865	0.0487
Rheum_A	1	1	-0.2429	0.0847	8.2244	0.0041
Coag	1	1	-0.1668	0.1002	2.7744	0.0958
Obesity	1	1	-0.0252	0.0675	0.1395	0.7088
WL	1	1	0.0759	0.0934	0.6606	0.4164

Fluid	1	1	0.0695	0.0607	1.3123	0.252
BLA	1	1	0.1949	0.1293	2.2736	0.1316
DA	1	1	0.0402	0.0618	0.4241	0.5149
Alcohol	1	1	0.1338	0.225	0.3538	0.552
Drug	1	1	-0.2849	0.3218	0.7837	0.376
Psycho	1	1	-0.2202	0.1505	2.1419	0.1433
Dep	1	1	-0.0182	0.0649	0.0787	0.7791

B. Non-Dual Beneficiaries-Nephropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.9044	0.0574	4627.81	<.0001
Cost_all_p	3	1	2.48E-02	4.20E-02	0.3502	0.554
Cost_all_p	2	1	-0.0257	0.0431	0.3544	0.5517
Cost_all_p	1	1	-0.00027	0.0443	0	0.9952
Cost_all_p	0	1	-0.0785	0.0543	2.0948	0.1478
sex	M	1	0.2369	0.0257	84.9435	<.0001
race_1	Other	1	0.0605	0.0629	0.9241	0.3364
race_1	Black	1	0.2207	0.0428	26.6355	<.0001
age_grp	80_over	1	0.5434	0.0351	239.954	<.0001
age_grp	75_to_7	1	0.3358	0.0368	83.1135	<.0001
age_grp	70_to_7	1	0.1686	0.0354	22.6742	<.0001
ip_tot_stay_1		1	-0.0358	0.0303	1.3998	0.2368
op_tot_stay_1		1	0.00843	0.00202	17.3768	<.0001
ov_1		1	0.00363	0.00196	3.4277	0.0641
snf_stay	1	1	-0.1606	0.0677	5.6277	0.0177
los_1		1	0.000622	0.00316	0.0387	0.8441
CHF	1	1	0.4046	0.0338	143.0927	<.0001
Arrhy	1	1	0.0449	0.0309	2.1072	0.1466
VD	1	1	0.0108	0.0349	0.0958	0.7569
PCD	1	1	0.1511	0.0614	6.0501	0.0139
PVD	1	1	0.1219	0.0315	15.002	0.0001
HPTN_NC	1	1	0.3378	0.0451	56.0204	<.0001
HPTN_C	1	1	0.1864	0.037	25.4013	<.0001
Para	1	1	-0.1417	0.1282	1.2216	0.269
OthND	1	1	-0.0588	0.0553	1.1332	0.2871
COPD	1	1	0.1049	0.0311	11.3646	0.0007
Hptothy	1	1	-0.0271	0.0298	0.8275	0.363
RF	1	1	2.0002	0.0337	3526.776	<.0001
LD	1	1	-0.0852	0.0605	1.9873	0.1586
PUD_NB	1	1	-0.011	0.1066	0.0105	0.9182
HIV	1	1	-0.2699	0.6111	0.1951	0.6587
Lymp	1	1	0.1446	0.1034	1.9583	0.1617
METS	1	1	0.1061	0.1064	0.9932	0.319
Tumor	1	1	0.0454	0.036	1.5884	0.2076
Rheum_A	1	1	-0.0276	0.0534	0.2668	0.6055
Coag	1	1	-0.0364	0.0596	0.3716	0.5421
Obesity	1	1	0.166	0.0451	13.5659	0.0002
WL	1	1	0.046	0.0609	0.5722	0.4494

Fluid	1	1	0.1603	0.0386	17.2568	<.0001
BLA	1	1	0.0915	0.0875	1.0937	0.2956
DA	1	1	0.1321	0.0399	10.9384	0.0009
Alcohol	1	1	0.2042	0.1463	1.9468	0.1629
Drug	1	1	9.56E-06	0.1869	0	1
Psycho	1	1	0.0128	0.0856	0.0223	0.8812
Dep	1	1	0.0642	0.0436	2.1674	0.141

C. Non-Dual Beneficiaries-Neuropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.5668	0.0564	4001.818	<.0001
Cost_all_p	3	1	1.54E-01	4.76E-02	10.4062	0.0013
Cost_all_p	2	1	0.2653	0.0472	31.589	<.0001
Cost_all_p	1	1	0.4001	0.0478	70.1636	<.0001
Cost_all_p	0	1	0.4103	0.0569	52.0026	<.0001
sex	M	1	0.0886	0.0269	10.82	0.001
race_1	Other	1	-0.2012	0.0734	7.509	0.0061
race_1	Black	1	0.1786	0.0455	15.421	<.0001
age_grp	80_over	1	0.1467	0.0367	15.9751	<.0001
age_grp	75_to_7	1	0.0797	0.0376	4.4856	0.0342
age_grp	70_to_7	1	0.0289	0.0349	0.686	0.4075
ip_tot_stay_1		1	-0.0417	0.0303	1.9013	0.1679
op_tot_stay_1		1	0.00325	0.00218	2.2204	0.1362
ov_1		1	0.0197	0.00187	110.5867	<.0001
snf_stay	1	1	0.1392	0.066	4.4486	0.0349
los_1		1	0.00583	0.00297	3.8442	0.0499
CHF	1	1	0.0921	0.0382	5.8211	0.0158
Arrhy	1	1	-0.0257	0.0328	0.6125	0.4338
VD	1	1	-0.0695	0.0376	3.4233	0.0643
PCD	1	1	-0.0422	0.0699	0.3647	0.5459
PVD	1	1	0.2731	0.032	72.7312	<.0001
HPTN_NC	1	1	-0.0361	0.0419	0.7409	0.3894
HPTN_C	1	1	0.0371	0.0423	0.7681	0.3808
Para	1	1	-0.00425	0.1197	0.0013	0.9717
OthND	1	1	0.1492	0.0531	7.8868	0.005
COPD	1	1	0.0476	0.0324	2.1629	0.1414
Hptothy	1	1	-0.00893	0.0308	0.0842	0.7717
RF	1	1	0.1706	0.0565	9.1038	0.0026
LD	1	1	0.0409	0.0585	0.4883	0.4847
PUD_NB	1	1	-0.024	0.1107	0.0471	0.8281
HIV	1	1	0.2092	0.519	0.1625	0.6868
Lymp	1	1	-0.2516	0.1224	4.2256	0.0398
METS	1	1	-0.00946	0.1149	0.0068	0.9344
Tumor	1	1	-0.16	0.0395	16.3879	<.0001
Rheum_A	1	1	0.0903	0.0513	3.0987	0.0784
Coag	1	1	-0.1283	0.0649	3.9041	0.0482
Obesity	1	1	0.2386	0.0444	28.8833	<.0001
WL	1	1	-0.0792	0.0661	1.4384	0.2304

Fluid	1	1	-0.00899	0.0423	0.0452	0.8316
BLA	1	1	-0.00062	0.0951	0	0.9948
DA	1	1	-0.00307	0.0435	0.005	0.9439
Alcohol	1	1	0.32	0.1396	5.2547	0.0219
Drug	1	1	0.4699	0.1465	10.2882	0.0013
Psycho	1	1	0.1072	0.0843	1.6172	0.2035
Dep	1	1	0.145	0.0425	11.6557	0.0006

D. Dual Beneficiaries-Retinopathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.5075	0.1695	428.0886	<.0001
mcaid_all	3	1	-3.14E-01	1.13E-01	7.7439	0.0054
mcaid_all	2	1	-0.38	0.1104	11.851	0.0006
mcaid_all	1	1	-0.4138	0.1167	12.5827	0.0004
mcaid_all	0	1	-0.0047	0.1011	0.0022	0.963
sex	F	1	0.0465	0.0801	0.3374	0.5613
race_1	Other	1	0.1719	0.0881	3.8037	0.0511
race_1	Black	1	0.2322	0.0922	6.3429	0.0118
age_grp	80_over	1	-0.1183	0.0986	1.4396	0.2302
age_grp	75_to_7	1	-0.0886	0.1032	0.7374	0.3905
age_grp	70_to_7	1	0.0614	0.0925	0.4407	0.5068
ip_tot_stay_1		1	0.0165	0.0864	0.0365	0.8484
op_tot_stay_1		1	0.00562	0.0051	1.2123	0.2709
ov_1		1	0.00074	0.00502	0.0218	0.8827
snf_stay	1	1	0.1104	0.1551	0.5063	0.4767
los_1		1	-0.0121	0.0112	1.1668	0.2801
CHF	1	1	0.0971	0.0957	1.0293	0.3103
Arrhy	1	1	-0.106	0.0942	1.2674	0.2603
VD	1	1	0.0946	0.1053	0.807	0.369
PCD	1	1	0.1885	0.1978	0.9079	0.3407
PVD	1	1	0.0693	0.0846	0.6702	0.413
HPTN_NC	1	1	0.3012	0.1356	4.9371	0.0263
HPTN_C	1	1	0.0713	0.1057	0.4556	0.4997
Para	1	1	0.3804	0.2175	3.0583	0.0803
OthND	1	1	0.1321	0.1268	1.0845	0.2977
COPD	1	1	-0.288	0.0875	10.834	0.001
Hptothy	1	1	0.033	0.0822	0.1611	0.6881
RF	1	1	0.3456	0.137	6.3578	0.0117
LD	1	1	0.0247	0.1432	0.0298	0.863
PUD_NB	1	1	-0.2069	0.2676	0.5979	0.4394
HIV	1	1	0.0512	0.7284	0.0049	0.944
Lymp	1	1	-0.2988	0.4575	0.4265	0.5137
METS	1	1	0.3958	0.3295	1.4429	0.2297
Tumor	1	1	-0.2624	0.1368	3.6772	0.0552
Rheum_A	1	1	-0.0651	0.1475	0.1947	0.659
Coag	1	1	-0.0841	0.1906	0.1945	0.6592
Obesity	1	1	0.0499	0.1202	0.1725	0.6779
WL	1	1	-0.4884	0.1919	6.4743	0.0109

Fluid	1	1	-0.0993	0.1107	0.8042	0.3698
BLA	1	1	-0.3243	0.2874	1.2728	0.2592
DA	1	1	0.0819	0.1072	0.5831	0.4451
Alcohol	1	1	0.2533	0.3326	0.5801	0.4463
Drug	1	1	0.2987	0.3302	0.8184	0.3657
Psycho	1	1	-0.1968	0.158	1.5528	0.2127
Dep	1	1	0.1121	0.0986	1.2946	0.2552

E. Dual Beneficiaries-Nephropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-3.0925	0.1251	611.127	<.0001
mcaid_all	3	1	-2.34E-01	8.46E-02	7.6415	0.0057
mcaid_all	2	1	-0.038	0.0781	0.2365	0.6267
mcaid_all	1	1	-0.0293	0.0811	0.1305	0.7179
mcaid_all	0	1	-0.2518	0.0808	9.7059	0.0018
sex	F	1	-0.1344	0.0566	5.6402	0.0176
race_1	Other	1	-0.1495	0.0684	4.7803	0.0288
race_1	Black	1	0.0829	0.0666	1.5479	0.2134
age_grp	80_over	1	0.3073	0.0694	19.5875	<.0001
age_grp	75_to_7	1	0.1622	0.0746	4.7352	0.0296
age_grp	70_to_7	1	-0.0731	0.0733	0.994	0.3188
ip_tot_stay_1		1	-0.0386	0.0483	0.6382	0.4244
op_tot_stay_1		1	0.00239	0.00354	0.4553	0.4998
ov_1		1	0.00187	0.0035	0.284	0.5941
snf_stay	1	1	-0.2168	0.104	4.3474	0.0371
los_1		1	-0.00297	0.00505	0.3467	0.556
CHF	1	1	0.3099	0.063	24.2123	<.0001
Arrhy	1	1	0.0883	0.0628	1.977	0.1597
VD	1	1	-0.00819	0.0736	0.0124	0.9114
PCD	1	1	0.1161	0.1269	0.8368	0.3603
PVD	1	1	0.1094	0.0587	3.4705	0.0625
HPTN_NC	1	1	0.245	0.0987	6.1622	0.0131
HPTN_C	1	1	0.2	0.0698	8.219	0.0041
Para	1	1	-0.1455	0.1823	0.6371	0.4248
OthND	1	1	0.0173	0.0886	0.0382	0.845
COPD	1	1	0.0605	0.0582	1.078	0.2992
Hptothy	1	1	0.0217	0.0587	0.1359	0.7124
RF	1	1	1.8962	0.0672	796.2964	<.0001
LD	1	1	0.18	0.099	3.3055	0.0691
PUD_NB	1	1	-0.1783	0.1816	0.964	0.3262
HIV	1	1	-1.3715	1.027	1.7832	0.1818
Lymp	1	1	-0.0301	0.2708	0.0123	0.9115
METS	1	1	0.0669	0.2326	0.0826	0.7738
Tumor	1	1	-0.00091	0.0872	0.0001	0.9917
Rheum_A	1	1	-0.255	0.1078	5.5978	0.018
Coag	1	1	-0.0687	0.1225	0.3141	0.5752
Obesity	1	1	0.1765	0.0833	4.4881	0.0341
WL	1	1	-0.0654	0.1096	0.356	0.5507

Fluid	1	1	0.2352	0.0697	11.3986	0.0007
BLA	1	1	0.1169	0.159	0.5408	0.4621
DA	1	1	0.0499	0.0748	0.444	0.5052
Alcohol	1	1	-0.0442	0.2604	0.0289	0.8651
Drug	1	1	0.3006	0.2337	1.6551	0.1983
Psycho	1	1	-0.3029	0.1103	7.5441	0.006
Dep	1	1	-0.0578	0.0718	0.6487	0.4206

F. Dual Beneficiaries-Neuropathy

Parameter		DF	Estimate	Std Err	Wald Chi-Sq	p-value
Intercept		1	-2.9468	0.1157	648.891	<.0001
mcaid_all	3	1	1.28E-01	8.02E-02	2.5488	0.1104
mcaid_all	2	1	0.1502	0.077	3.8025	0.0512
mcaid_all	1	1	-0.0914	0.0837	1.1929	0.2747
mcaid_all	0	1	-0.0376	0.0788	0.2278	0.6331
sex	F	1	0.0394	0.0562	0.4917	0.4832
race_1	Other	1	-0.0833	0.0644	1.6711	0.1961
race_1	Black	1	-0.1345	0.0687	3.8356	0.0502
age_grp	80_over	1	-0.1197	0.0704	2.8913	0.0891
age_grp	75_to_7	1	0.0226	0.0715	0.0997	0.7521
age_grp	70_to_7	1	0.0753	0.0655	1.3215	0.2503
ip_tot_stay_1		1	0.0684	0.0495	1.9058	0.1674
op_tot_stay_1		1	0.00264	0.00344	0.588	0.4432
ov_1		1	0.0167	0.00306	29.8299	<.0001
snf_stay	1	1	-0.0451	0.1023	0.1943	0.6594
los_1		1	-0.0104	0.00623	2.7776	0.0956
CHF	1	1	0.2221	0.0631	12.4045	0.0004
Arrhy	1	1	-0.0945	0.0632	2.2336	0.135
VD	1	1	-0.0407	0.0724	0.3171	0.5733
PCD	1	1	-0.0406	0.1297	0.0978	0.7545
PVD	1	1	0.3061	0.0562	29.6705	<.0001
HPTN_NC	1	1	-0.013	0.0876	0.022	0.882
HPTN_C	1	1	0.0976	0.0713	1.8739	0.171
Para	1	1	-0.00223	0.1677	0.0002	0.9894
OthND	1	1	0.0481	0.0868	0.3068	0.5797
COPD	1	1	0.0724	0.0558	1.6838	0.1944
Hptothy	1	1	-0.0366	0.0573	0.4091	0.5225
RF	1	1	0.2277	0.0966	5.5601	0.0184
LD	1	1	-0.0879	0.0995	0.7801	0.3771
PUD_NB	1	1	-0.00179	0.1646	0.0001	0.9913
HIV	1	1	0.3466	0.4786	0.5246	0.4689
Lymp	1	1	0.1785	0.2458	0.5273	0.4677
METS	1	1	-0.0691	0.2371	0.0851	0.7705
Tumor	1	1	-0.1085	0.0871	1.5517	0.2129
Rheum_A	1	1	0.1947	0.089	4.7822	0.0288
Coag	1	1	0.17	0.1129	2.2678	0.1321
Obesity	1	1	0.2812	0.0766	13.4802	0.0002
WL	1	1	-0.0584	0.1079	0.2925	0.5886

Fluid	1	1	0.1477	0.07	4.4536	0.0348
BLA	1	1	-0.2642	0.1772	2.2227	0.136
DA	1	1	0.0456	0.0732	0.3881	0.5333
Alcohol	1	1	-0.0566	0.2526	0.0501	0.8228
Drug	1	1	0.5004	0.1922	6.7814	0.0092
Psycho	1	1	-0.3031	0.1087	7.7725	0.0053
Dep	1	1	0.1999	0.065	9.4514	0.0021